

The Emergence of Reciprocity through Contrast and Dissonance

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Revision Date: 8/14/98

This work was supported in part by the National Science Foundation, NSF IGERT and NSF GRT9354995, and by the Center for Computational Analysis of Social and Organizational Systems (CASOS)

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Abstract

Within groups of interacting individuals, relationships are formed in accordance to predictions of homophily. However, group composition often dictates the kind of homophily found: choice homophily or induced homophily. In differentiated groups with evolving relationships, we can easily imagine interactions occurring by choice then eventually by an apparently random process due to the increasing homogeneity of the group. In this paper, a dynamic model of group interaction is presented. By the nature of the model, virtual groups are initially differentiated and eventually reach a state of stability, sometimes complete homogeneity. Interaction is primarily constrained by two cognitive mechanisms: contrast biases and dissonance reduction, a la Heiderian balance. The presence of mutual, affective relationships defined by frequent interaction are shown to be prevalent under the contrast condition. Furthermore, our findings show that the formation of strong triads, consisting only of strong reciprocal ties, are driven by contrast while weak and transitive triads are more driven by balance. Balance, also, tends to induce higher degrees of centralization while contrast has the opposite effect.

INTRODUCTION

“Birds of a feather flock together.” This phrase is the essence of a phenomenon known as homophily, the tendency of individuals in friendship and other social relationships to be similar to one another. The existence of homophily has been repeatedly confirmed. Similarities between individuals along specific dimensions have often been used to demonstrate and predict structures, like dyads and triads, in various kinds of groups (McPherson and Smith-Lovin, 1987)(Marsden, 1988)(Newcomb, 1961). However, explorations on the dynamic process which eventually result in these homophilous relationships are less common; the particular ways in which impressions and affect form remain largely unknown. Generally lesser degrees of differentiation within observed groups can dispel the need for understanding this evolution process and allows one to rather focus on the outcomes. That is, dyads in homogenous groups will undoubtedly exhibit strong degrees of homophily. However, in such groups, the process that determines why certain relationships form and others do not is not very clear considering each individual is already similar to everyone else. In a highly differentiated group, the process can be more complex and interesting; relationships can be motivated by specific similarities while the group merely sets the context in which the relationship formation process takes place. McPherson and Smith-Lovin labeled the types of homophily, found in groups, as *induced homophily*, for homogenous groups, and *choice homophily*, for differentiated groups (McPherson and Smith-Lovin, 1987). Induced homophily refers to the observation that within homogenous groups it is difficult to determine the dimensions along which individuals perceive similarity to one another. In the differentiated groups, the dimensions of similarity are more salient to group members. Hence, individuals appear to consciously choose those with whom they interact.

It is often the case that both types of homophilies are found. Elements of culture, whether based on knowledge or attitudes, initially diffuse through avenues of choice homophily and ultimately by the imposition of a saturated group (i.e. influence through induced homophily) (Coleman, 1957). More people accepting an idea or attitude increases the likelihood that the minority will be co-opted. However, initial contagion effects are induced by specific structural properties such as social proximity in the form of distance or structural equivalence.

In everyday life, we observe that the dimensions along which individuals perceive similarity with others tend to be non-physical as often as they are physical (McPherson and Smith-Lovin, 1987). Similarities among friends can be based on dimensions such as interests,

opinions, status, and education as well as visible physical characteristics such as gender and ethnicity (Banta and Hetherington, 1963)(Izard, 1960)(Miller et al, 1966). Verbal exchanges and other cues can be similarity-enhancing signals. Furthermore, these signals often carry valence inducing positive relationships and negative ones as well (Johnsen, 1986).

Friendship and other affective relationships are based on attraction, physical or mental. The similarity-attraction relationship, that in turn leads to interaction and promotes the formation of affective relationships, has received wide attention from social psychology. Aside from Newcomb's field study and replications (Curry and Emerson 1970), studies have shown similarity-induced attraction in situations when attitudes are transmitted (Byrne and Clore, 1966)(Hodges and Byrne, 1972), in face to face interactions involving a confederate, and in real life situations (Brewer and Brewer, 1968). The relationship holds for a variety of populations including children (Byrne and Griffitt, 1966), senior citizens (Griffitt et al, 1972), individuals of low socioeconomic status individuals such as Job Corps Trainees and alcoholic and schizophrenic hospital patients (Byrne et al, 1969), and Japanese, Indian, and Mexican students (Byrne et al, 1971). Other studies have focused on dyadic relationships; couples were found to be similar on a variety of characteristics (Burgess and Wallin, 1943). That interaction itself results in increased attraction, hence promoting the cycle, has been empirically verified (Zajonc, 1968).

Several mechanisms for the formation of attraction-similarity and hence affective relationships have been researched. In this paper, we examine the effects of three cognitive mechanisms involved in the formation of relationships using a computational interaction model and strive to understand the process by which these mechanisms result in the formation of enduring ties. Accordingly, the dynamics induced by these mechanisms are anticipated to determine the nature of strong tie formation. The first mechanism is an implementation of Heider's balance theory. The second mechanism is derived from cognitive framing in which the perception of in-groups and out-groups occur through the recognition of similarities and differences between individuals in the immediate context or environment. We refer to the effect of this mechanism as *contrast homophily*, or simply contrast, emphasizing the enhancement of similarity between two individuals due to their differences with other individuals. The third is simply social influence operating on strongly opposing traits or attitudes; this is detailed below.

While prior research has singly examined these theories of social interaction, here, we synthesize the theories and examine interaction and relationship formation across a set of synthesized models. The virtual experiments described in this research allow us to determine differences and/or similarities across models each based on a unique combination of the three mechanisms. The eight models entail the following mechanisms: none save the default interaction model, balance only, contrast only, influence only, contrast/balance, contrast/influence, balance/influence, contrast/balance/influence.

THE INTERACTION MODEL

The baseline computational model of interaction is adapted from Carley's construct model (Carley, 1990)(Carley, 1991). In the model, individuals embedded in a community continuously share information until cultural homogeneity is achieved. That is, through interaction and exchange of information, individuals become more and more similar. However, cultural homogeneity need not reflect similarities in knowledge. Interaction often induces similarities between beliefs and attitudes across individuals (Heider, 1958)(Homans, 1961)(Newcomb, 1961). In the model for this research, individuals exchange not only information, but beliefs, attitudes, and norms: anything that is capable of inducing a perception of similarity. Furthermore, as homophily predicts, individuals who already perceive themselves as similar will tend send and receive such signals to one another. According to Newcomb, an individual holding a strong attitude or belief is likely to perceive similarity with another individual of the same disposition. Hence, individuals who share similar traits will tend to interact more often with one another. For this model, we define a group of N individuals that have the opportunity to interact with one another. Each individual i is represented by a characteristics vector F of size K . Each position in the vector takes on values from the set $\{0, 1\}$. A value of 1 refers to the existence of any attribute that promotes the perception of similarity between individuals. A 0 does not imply an opposite characteristic, but merely its absence.¹ No labels are given to any of the characteristics leaving them context-free. Variations in degree of

¹ Another interpretation recognizes "0", or absence, as a similarity enhancing signal. Implementing this interpretation in the model largely affects the impact of contrast. Network structures become less varied across models, but however become more sensitive to extreme levels of contrast, or contrast weight (explained below). Furthermore, the effects of the contrast/balance and contrast/balance/influence models vary and sometimes reverse between the two interpretations.

attitude can be achieved by considering that it possible for more than one characteristic to be associated with a single attitude or trait. That is, “111” could imply a strong disposition on a single attitude and “110” could imply a slightly weaker disposition.

Two types of characteristics are modeled: independent and mutually exclusive. The presence of an independent characteristic is, as the name implies, independent of any other characteristic. Generally, we can think of these as traits which do not have an explicitly negative counterpart (e.g. plays soccer and does not play soccer are represented by 1 and 0). Mutually exclusive characteristics come in pairs. If two positions on the characteristic vector are mutually exclusive, then both cannot be 1 at the same time. These reflect attitudes or characteristics that cannot co-occur. They can refer attitudes of opposite valence (e.g. “loves soccer” vs. “hates soccer” or “abortion is good” vs. “abortion is evil”) or others that are without valence but are still exclusive (e.g. being Asian vs. being Caucasian). The number of characteristics that represent mutually exclusive pairs is one of the model’s parameters.

The composition of an individual, at any given time t for characteristic k , is denoted by $F_{ik}(t)$; this specific notation is used in order to maintain consistency with the original construct model.

Interactions occur in discrete, lock-stepped rounds; for simplicity’s sake, individuals interact concurrently in batches. Each individual elects to interact with another individual with whom s/he perceives similarity and exchanges a bit of information or shares his or her belief and attitude. Again, if one wishes to consider degrees of traits and dispositions, the transfer represents an influence process (i.e. individual A makes individual B feel more strongly towards a shared attitude X). The basic mode of one-to-one interaction has been extended to two other modes, which are explained later.

Nominations for interaction are made probabilistically; more similar individuals are likely to associate with one another. However, this is not necessarily inevitable. The formalization of this appears as:

$$P_{ij}(t) = \frac{\sum_{k=1}^K F_{ik}(t) F_{jk}(t)}{\sum_{h=1}^N \sum_{k=1}^K F_{ik}(t) F_{hk}(t)} \quad (1)$$

According to construct, this is the definition of *relative similarity*. The probability, P , of ego, i , interacting with alter, j , at time t is the sum of the information they share divided by the total instances of information shared between i and everyone else including j ; absolute similarity ratings are meaningless here. During interaction, an individual will receive a signal (i.e. bit of information) from the partner, regardless of whether the information is already known or not. This construction process reflects what is called “positive balance” posited by Newcomb (1968). The exchange that occurs during the interaction can reflect the adoption of attitudes. The interaction between two individuals is based on similarity and, according to homophily, correlated with liking. Hence, the exchange of a characteristic represents this “positive balance” process. However, “positive balance” implies a probability of influence as a function of similarity; that is, the more A likes B, the more likely it is that A will agree with B’s attitude toward X. The dynamic in this model is obviously different. Interaction, already being a function of similarity, automatically allows for non-characteristics (value = 0) to become a characteristic (value = 1). Hence, influence as a function of similarity is here implemented only for mutually-exclusive characteristics and in the operationalization of balance (i.e. X is another person).

Information passing in this model is perfect and reliable; misinterpretations, forgetting, and discovery do not occur. The groups can reach a state in which all characteristics are shared in the case of only independent characteristics, distinct subgroups emerge in the presence of some exclusive characteristics, or the interactions do not reach equilibrium and remain in constant flux under the balance condition as explained below.

An Example of Construct

Individuals A, B, and C are represented by the characteristic vectors 1100, 1000, and 0001.

At round 1: A is randomly selected as an initiator of interaction. A has similarity only to B (he shares no characteristics with C) and interacts with B. The exchange of characteristics goes in both directions during interaction. Each, the initiator and receiver, will send a signal of a characteristic. So, A sends 1 from position/characteristic 1, which B already has. B sends the 1 from position/characteristic 4 which A accepts. B could have instead send 1 from position 1. So at the end of the first round, A is now characterized by 1101. For the default mode of

interaction, only pairs of individuals can interact per round so C does not interact. For this example, we consider the entire group to be comprised of the three individuals A, B, and C.

At round 2: C is randomly selected as the initiator. His similarity to A is one and his similarity to B is one. Hence, he has a fifty-fifty chance of interacting with either of them and selects A. Consequently, he receives the characteristic at position 2 and is now represented by 1101.

Clearly, one can see that, through basic construct, the group will eventually reach homogeneity in their characteristics.

BALANCE

Heider's theory of balance basically predicts the formation of ties in such a manner as to minimize dissonance for the participants (Heider, 1958). According to the theory, ties can represent either positive or negative affect, and the product of such affective ties in a triad must be positive. Legitimate sets of relations consist of three individuals liking one another and one individual disliking two who have positive affect for one another. The situation in which one individual likes two others who dislike one another is an unbalanced, dissonant state that requires resolution.

Liking and disliking can be seen as similarity reinforcing and dissolving mechanisms. Individuals who like one another will strive to agree along various opinions and attitudes while those who dislike another, wishing to maintain this state, may not do so. In fact, signals of intentional dislike can involve deliberate disagreements and/or attitude changes: "Well if he thinks that, then I won't!" Hence, individuals will place positive and negative values on these differences (Homans, 1961).

Heiderian balance includes a dynamic excluded from Newcomb's positive balance: negative balance. Let's say, A likes B and then B decides to like C. Under negative balance, the third person C can be so different or disliked by A that no matter how much A likes B, he cannot have positive affect towards C. In order to reduce dissonance, he will distance himself from friend B.

While balance refers to the state of ties, the definition of what a "tie" really is in network study has not been formalized. As interactions form the bases of ties, it is appropriate to apply

balance at the level of interaction. Hence, we extend the notion of balance allowing for dissonance reduction to occur for each interaction process rather than imposing balance on the final emergent network.

In the model, an individual will modify his or her affect by adjusting the traits/characteristics vector in an effort to reduce dissonance by altering similarity with another individual. For each nomination, the interacting individual or ego observes the third party with whom the nominee, or immediate other, had interacted in the **prior** round. The greater the similarity between ego and the other, the higher the probability of ego becoming more similar to the third party of the prior round. The greater the dissimilarity between ego and the third, the higher the probability of ego becoming more dissimilar from the currently nominated individual. Heider discusses induction of liking across similar individuals. Here, we correlate similar characteristics with higher probability of interaction, which is labeled by observers as “liking”. It has been shown that individuals interacting with highly attractive individuals will tend to agree with those individuals (Newcomb, 1961). Individuals that distance themselves from those who are connected to disliked individuals exhibit what is known as value heterophoby; the disagreement in this case is the relationship or interaction with the third party (Johnsen, 1986).

Specifically, the probability of ego reducing similarity with the other is equal to the number of differing characteristics with the third party divided by the sum of this count and the number of the information shared with the immediate alter. If reduction of similarity occurs, ego removes a randomly selected trait shared with the immediate other. If similarity enhancement occurs, ego adopts a randomly selected piece of trait that is shared between the other and third but not between the ego and other, all in an effort to increase similarity across all three individuals. Choosing to be more similar, hence increasing positive affect, results in positive balance. Note that the enabling of the balance mechanism in the model will not necessarily induce positive balance. As we shall see, negative balance occurs as well as positive.

Example of Balance in the Interaction:

Consider a group of individuals A, B, and C whose characteristic vectors are 1110, 1011, and 1101, respectively.

While explicit ties are neither created nor eliminated, the probability of interactions between these individuals becomes adjusted. For these analyses, the presence of a tie is dependent solely on the frequency of interactions; this is explained later. If C chooses to acquire the characteristic shared by A and B, then his probability of interacting with either of them increases. If we consider a group with more than three actors, these probabilities become relevant in inducing A, B, and C to form a triad as measured from the final tallies of interactions. Hence, balancing interactions will ultimately lead to balanced ties.

CONTRAST

How does one determine which characteristics are the foci of homophilous relationships? Often, the answer depends on the context. In the workplace, status, sex, and education often drive homophily. Among university students, similar intellectual or recreational interests promote homophilous relationships. In differentiated environments, individuals may even psychologically construct the context. This is the basis of *contrast homophily*. Consider a cocktail party. At a given time, there are two women and two men. While there may be stronger affinity between individuals of like gender, this can generally be imagined to be not too strong, and the interactions are distributed almost evenly. At another given time, we observe two women and ten men. It is likely that the two women will tend to feel even stronger affinity for one another than for any of the men. Furthermore, this affinity will be stronger than those between the men. One can reverse the situation, two men and ten women, and predict a similar effect. The relationships between the minority individuals are driven by overt and unexpected contrasts between themselves and the majority. Furthermore, there need not be an explicit reason as to why the contrast exists. In fact, the non-existence of an obvious rationale can enhance the strength of contrast. Given a rationale, individuals might feel empowered to react contrary to their reactions to the contrast. For now, we avoid more complex effects such as minority individuals intentionally remaining non-interactive with one other for a specific agenda (e.g. to demonstrate non-cliquey behavior). Also, these contrasts need not be physical in nature and can be defined by differential beliefs and opinions that have been communicated. Contrast homophily is, therefore, a specification of the social comparison process through which individuals assess higher similarity to certain individuals through strong differences with others.

A host of anecdotal evidence supports this claim: social segregation along racial, cultural, and sub-cultural differences, etc.

As differences become more salient, similarities will be less emphasized. This is consistent with rational decision-making behavior. Individuals re-frame choices such that the common denominators are not included in the mental calculations (Dawes, 1988)(Kahneman and Tversky, 1979, 1986). Under contrast homophily, the importance of an attribute is discounted or weighted down by the degree to which it is representative of everyone in the group.

The contrast induces the perception of in-groups and out-groups. An individual perceiving stronger contrast will identify himself with the minority group. Consequently, members of the minority groups are likely to expect similar framing of the situation from other members of the minority group and hence expect similar propensity for interaction. The contrast, and not their similarity per se, becomes a visible symbol inducing the expectation of interaction with others on one side of the contrast. These individuals will then share what is known as a consensual frame of reference as they have self-categorized, or performed status-organization on, themselves (Stryker, 1980)(Goffman, 1974)(Berger et al, 1977).

The contrast dynamics closely follow Mead's model/template of interaction in which assessment and identification of self is directly tied to the perception of signals from others (Mead, 1938). Signals from other individuals can either be intentional or non-intentional. For instance, people may dress a certain way to attract others with similar tastes associated with the style. The interaction between individuals, who contrast along some dimension with a majority group, also represents a signal of similarity. Onlookers will view individuals who interact as more similar. This occurs in the model as those who interact do become similar. Generalized others are described by the dimensions that induce the contrast. So the majority group and minority groups each represent a generalized other only for those in the minority group. Contrast induces categorization of individuals in the structuring process of a social situation. (Turner, 1988). These individuals form what Heider describes as cognitive units (Heider, 1958). In this case, the units are the in-group and out-groups.

Differentiation is known to limit the kinds and number of interactions that occur in face-to-face associations (Blau, 1977). Contrast can promote the formation of sub-groups differentiated along highly contrasting dimensions. However, contrast can also increase the degree to which groups are initially heterogeneous, especially when contrasting dimensions cross

potential sub-groups. Heterogeneity defies differentiation and should increase the probability of inter-group relations and interactions (Blau, 1977); in the model, this will result in the dissolution of sub-groups. Since the groups for this research are stochastically generated and heterogeneous, it seems more likely that contrast will ultimately promote homogeneity; the group will not stabilize into multiple sub-groups.

In the model, contrast homophily is achieved by modifying the formulation of relative similarity (Carley, 1991):

$$w_{ik} = \frac{1}{N} \frac{1}{f_{jk}(t) f_{ik}(t)} \quad \text{and} \quad P_{ij}(t) = \frac{\sum_k^K F_{ik}(t) f_{jk}(t) w_{ik}}{\sum_{h=1}^N \sum_{k=1}^K F_{ik}(t) f_{hk}(t) w_{ik}} \quad (3)$$

where $w_k \in [0,1]$.

A weight for characteristic k is determined by the inverse of number of times that characteristic is shared between i and the group, raised to α power. It will be shown that α needs to be $\alpha \geq 2$ under most conditions for the contrast to affect randomly generated groups. Hence, traits shared with a relatively small number of individuals will receive stronger weight in the calculation of similarity.

Example of Contrast:

Consider the following group:

person #	attributes vector
0	1 1 1 0
1	1 1 1 0
2	1 1 0 0
3	1 0 0 0
4	1 0 0 0
5	1 0 0 0

Given $\alpha = 2$, the weights for each attribute for person #1 are 0.04, 0.25, 1.0, and 0. Thus, #1's contrast-based similarities are, with #0, 1.29, with #2, 0.29, and with #3, #4, and #5, 0.04. Hence, #1 is over four times more likely to interact with #0 than s/he is with #2, and 32 times more likely to interact with #0 than s/he is with #3 to #5. The attribute that is common to

everyone (i.e. the first position of the vector) is heavily discounted. For the virtual experiments, we allow vary the α exponent to take on the values 1 and 2.

Note that while contrast may strongly predict the perception of group boundaries, realistically, it does not necessarily predict interaction. In the four person cocktail party example, it is easy to imagine that the two men will be likely to interact more with the women rather than to each other due to the context. However, context dependence is not something that is accounted for in the current model.

INFLUENCE

One other dynamic is introduced to address positive balance. Under the model's default interaction process, the non-existent characteristic 0 represents neutrality and easily becomes a 1 once an interaction takes place. When an individual interacts with another and sends the signal representing a characteristic to a recipient who does not have the characteristic, the recipient will accept it with probability 1.0. What happens when the sent signal represents a mutually exclusive characteristic? For two individuals maintaining opposing values, there must exist a probability that one will be able to influence the other. The influence parameter determines whether this probability remains 0 or equals the individuals' similarity score, based on either contrast or relative similarity. Thus, under influence, it is possible for one of a pair of mutually exclusive characteristics to change to the other in the pair; that is, a "10" pair turns into "01". The higher similarity confers a greater probability of influence. This dynamic is also present in dissonance reduction. If one of the characteristics that an individual needs to adopt in order to positively reduce dissonance is a mutually exclusive one and the individual maintains the other characteristics, the probability of his switching is equal to the similarity score.

Considerable research supports the notion of influence being more probable given a higher level of attraction, hence similarity. Conformity to opinions and judgments have been found to be positively associated with liking (Kiesler and Kiesler, 1969) as well as imitative behavior and preferences (Lott and Lott, 1968)(Mischel and Grusec, 1966). Furthermore, influence operating on either unbiased or strongly opposing attitudes is a form of conflict or dissonance resolution and promotes overall conformity (Moscovici, 1985).

MODEL PARAMETERS

We have already discussed N (number of individuals in the group), K (number of information bits per individual) and γ (the strength of contrast). Since we vary the situations in which balance, contrast, and influence are enabled, we specify three flags, the balance flag (B), contrast flag (C), and influence flag (I). The enabling of balance does not necessarily induce positive balance; both positive and negative dissonance reductions are possible.

MODES OF INTERACTION

The basic mode of interaction involves an individual selecting someone from the set of those not engaged. Two additional modes of interaction, perhaps more realistic, have been added, and their effects are also analyzed. The second, additional mode relaxes the one-to-one interaction constraints on the group. Individuals in the basic mode are only allowed to interact with one other individual at a time. In the second mode, individuals can interact with more than one person at a time. A single interaction need not represent an actual verbal exchange. One can assume a different time scale in which a single round of interaction represents a substantial period of time. With a different scale, we can assume the reduction of interactions to the smallest of exchanges (e.g. a knowing look) such that multiple exchanges can occur almost simultaneously. Finally, the third mode constrains interaction the most. An individual selects someone from the whole group and attempts to interact with that person. If the selected individual is already engaged, the ego misses the chance for an interaction and must try again later. The purpose behind the second and third modes is to have interaction more strongly reflect homophilous tendencies between the individuals. If one individual has very strong affinity towards another, it seems reasonable that s/he will forego interaction rather than interacting with a less-liked individual. The numerical designations are made in the order of interaction frequency: 0 = “the third, most constraining mode”, 1 = “the basic mode”, and 2 = “the multiple, least constraining interaction mode”.

Graphical Representation

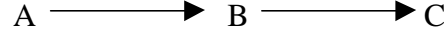
Mode 0 – Most constraining – A chooses B but B is already engaged with C so A does not interact with anyone that round.



Mode 1 – Default – since B and C are already engaged, A does not even consider interacting with either and chooses from the set of available others and chooses D.



Mode 2 – Multiple Interactions – A can interact with B while B is interacting with C.



Furthermore, we vary the initial percentage (P) of characteristics in the groups. Homogeneity is defined as the percentage 1-bits in the characteristics vectors F across all individuals. For example, 30% means that for $N = 20$ individuals with characteristics vectors of size $K = 10$, 60 bits will be 1 and 140 will be 0. Varying this parameter will allow us to determine whether the initial level of homogeneity affects the number of relationships that emerge. Finally, we vary the percentage of characteristics that are mutually exclusive characteristics with parameter X . With this parameter, we seek to understand whether the type of characteristics is significant in the formative process.

Table 1. Description of Model Parameters

Description	Symbol	Values
Groups size	N	10, 20, 30
Characteristic/Knowledge base size	K	6, 9, 12
Mode of Interaction	M	0, 1, 2
Contrast homophily flag	C	0, 1
Strength or Weight of contrast	W	1, 2
Balance flag	B	0, 1
Percentage initial homogeneity	P	30%, 50%
Mutually Exclusive Characteristics	X	0, ~50%, ~100% *
Social Influence	I	0, 1
Total Conditions		1620

*These are approximate since certain values of K are odd and mutually exclusive characteristics occur in pairs.

Since the Monte Carlo technique is employed in the analysis, the composition of the vectors is randomly generated for all runs with one constraint. Group must be “fully-connected”; individuals must have a common characteristic with at least one other such that eventually the group will reach cultural homogeneity under non-exclusivity and no balance. Each combination of parameters represents a separate experimental condition for which 10 stochastic runs have

been made. In other words, 540 (for non-contrast) + 2*540 (for each level of contrast) = 1620 sets of runs are performed, and the resulting data set consists of 16200 observations.

RESULTS

We first examine the general behavior of the model by focusing on several key measurements; following this, we will examine how the model compares to empirical data. The first four quantities are non-network measures and refer to general characteristics of the final group. The first is the duration of activity, proxy for time, until *stability* is reached or activity exceeds 999 rounds at which point we assume instability. Stability is declared when no information is exchanged for 50 rounds. We are also interested in the distribution of characteristics in the final state and measure the degree of *homogeneity*. Understanding the factors that determine the degree to which characteristics are shared is fundamental to the study of groups and homophilous relationships. Since multiple groups may emerge at the time to stability, we examine the conditions that drive this splintering and attempt to understand what determines the number of *sub-groups* that emerge. We are also interested in the types of dissonance reduction. We examine the parameters which determine whether positive balance is dominant or negative balance occurs more often. This is accomplished by analyzing the difference between positive and negative balance.

The next set of measures examines properties of the emergent network. Before addressing these measures, we need to define what a network tie is in this model. During group activity, all directed interactions between individuals are tallied in a matrix; when actor i interacts with actor j , cell (i,j) of the interaction matrix is incremented by one. The final matrix represents a history of interactions. From this, directed ties are obtained by dichotomizing the matrix using the mean interaction score which is $(\text{the sum of all interactions}) / n*(n-1)$. Hence, the cut-off and definition of a tie varies according to the distribution of interaction scores.

The first network property we examine is *reciprocity* using the count of observed reciprocal dyads. In a differentiated environment, some individuals tend to form differentiated relationships, some of which will be strong, reciprocal dyads while others maintain asymmetric or no relations at all. The extent to which strongly reciprocal ties emerge across the experimental conditions is examined. Since it is necessary to measure the degree of reciprocity

against a null-model, we compare the reciprocities of the emergent groups with those of randomly generated networks of corresponding size and densities.

We also examine the emergence of the structure beyond the dyad, which is the triad. Given the implicit influence of balance to generate transitive ties, we measure the degree to which *transitive*, *weak*, and *strong triads* form. A transitive triad is one in which there exists a set of directed relations that are transitive. By this definition, more than one transitive triad can exist for a threesome, given reciprocal ties. A weak triad is simply the set of any relations involving three people. A strong triad consists of individuals who reciprocate Simmelian ties to one another.

We examine how the networks generated from the model compare with a single *empirical network* and determine the parameters that drive or minimize the differences between the empirical and the generated networks. Finally, we measure *centralization* and examine how contrast, balance, and influence drive this network property.

For all of the regressions, in order to maintain simplicity of explanation while sacrificing some power in the tests, we use only the single parameters as well as the two- and three-way interactions between contrast, balance, and influence. These interactions are included since they are comprised of the effects that are the foci of this study. The regressions are also unstandardized since the parameters are scaled similarly and we desire to know the effects of the absolute increments in the parameter values. For each regression model, we focus on those predictors with strongest effects (i.e. highest t-statistic), with exception of the interaction terms whose interpretations are problematic when both the main and the interaction terms are significant. Therefore, accompanying each regression model is an analysis of variance table that exposes the interactive effects of influence, balance, and contrast, along with its weights.

TIME TO STABILITY

We define stability as the time at which exchange of traits/characteristics ceases. At this point, the group has either reached cultural homogeneity and all share the same traits or has been divided into sub-groups. We use the number of rounds of interaction that occur as our proxy for time as the events in the model are discrete. Furthermore, the group may not necessarily reach stability; under certain conditions, the group remains in state of constant interaction. We have set the time limit to be 999 rounds of interaction. At this point, we classify the group as unstable.

We regress time against the individual parameters and the interactions. Time to stability is transformed using a log10 function in order to satisfy the assumptions of normality.

Table 2a. Regression on Log10(Time to Stability + 1)

Predictor	Coef	StDev	T	P	
Constant	0.56192	0.02885	19.48	0.000	
N	0.0183412	0.0004360	42.07	0.000	
K	0.066540	0.001459	45.60	0.000	
M	-0.216821	0.004358	-49.75	0.000	
C	-0.07518	0.01446	-5.20	0.000	
W	0.177845	0.008717	20.40	0.000	
B	0.63023	0.01591	39.60	0.000	
P	-0.0037559	0.0004380	-8.57	0.000	
X	0.0020173	0.0001075	18.76	0.000	
I	0.46414	0.01795	25.86	0.000	
CB	-0.16758	0.01949	-8.60	0.000	
BI	-0.95643	0.02516	-38.01	0.000	
CI	0.63703	0.02179	29.23	0.000	
CBI	-0.01609	0.03082	-0.52	0.602	
S = 0.4529		R-Sq = 53.7%		R-Sq(adj) = 53.6%	
Source	DF	SS	MS	F	P
Regression	13	3846.55	295.89	1442.31	0.000
Error	16186	3320.55	0.21		

The bold-typed rows highlight the predictors with the strongest significance and often highest coefficient. We focus our attention to these predictors and find that size (N), characteristics (K), and multiple interactions (M) are the primary determinants of time to stability. This is fairly intuitive: the greater the number of characteristics that need to be exchanged, the longer it takes for everyone to share those characteristics. Increasing the rate of interactions would clearly reduce the time. We also observe that balance (B) and influence (I) are have significant and strong effects. However, since they are involved in significant interactions, the interpretation of the coefficients is problematic. A straight t-test ($t = 45.78$) shows us that indeed influence has a prominent effect as do balance ($t = 12.644$) and contrast ($t = 16.516$).

Table 2b. Analysis of Variance for Log10(Time to Stability + 1)

IBCW	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev				
				-----+-----+-----+-----+-----				
None	1620	1.4445	0.3357	(*)				
__C1	1620	1.4511	0.3383	(*)				
__C2	1620	1.4647	0.3382	(*)				
_B__	1620	2.0743	0.6817			(*)		
_BC1	1620	1.9317	0.7405		(*)			
_BC2	1620	1.9098	0.7053		(*)			
I__	1080	1.9621	0.4416		(*)			
I_C1	1080	2.4491	0.5080			(*)		
I_C2	1080	2.7770	0.4295				(*)	
IB__	1080	1.6356	0.3361	(*)				
IBC1	1080	1.8149	0.5087		(*)			
IBC2	1080	2.3908	0.7174			(*)		
Pooled StDev = 0.5355					1.60	2.00	2.40	2.80

The “IBCW” column of the ANOVA table corresponds to the enabling of the focal parameters: influence (I), Heider’s balance (B), contrast (C), and weight of contrast (W), positioned in each of the columns, respectively. So, the third row, “__C1” corresponds to the condition in which contrast with weight 1 was enabled while balance and the fourth row, “_B__” corresponds to the conditions in which balance was enabled (B = 1), contrast was disabled (C = 0). The highlighted rows merely serve to separate groups of the IBCW levels and do not signify anything about the data. Also note that the levels are sometimes re-ordered as BICW. The ordering that best organizes the data is used.

The display of means on the right contains an interesting pattern. While contrast in general serves to increase the time to stability, balance has varied effects under different conditions of contrast. In the absence of any contrast effect, balance serves to drastically increase the time to stability suggesting that the negative type of balance occurs more often than the positive; we infer this by comparing levels “None” and “_B__”. However, under influence, the effect is severely reduced: influence induces more positive balance which serves to increase homogeneity and stability by making triads become more similar (“_B__” vs. “IB__”). An alternative hypothesis is that negative balance merely counters the differentiating property of influence; an individual who becomes influenced may suddenly decide to relinquish that newly acquired attitude and becomes impressionable on that characteristic. As we shall see later, there is more evidence for the former dynamic.

Under positive balance, individuals become more similar to one another more quickly, and the converse is true when negative balance is the predominant dynamic. However, we see that this effect is diluted under the increasing conditions of contrast. This finding implies that either less of the negative balance is occurring or more of the positive or a combination of both. In subsequent analyses, we see that more positive balance occurs under contrast. Intuitively, this makes sense; contrast induces stronger feelings of similarity with relevant others hence increasing the probability that a positive type of dissonance reduction will occur rather than the negative.

Under influence, individuals are capable of changing characteristics and end up maintaining the opposite attitude or trait. Hence, this introduces a dynamic that reverses the trajectory towards stability. When individuals change attitudes they change their similarities with contacts and open opportunities or increase probabilities of interactions with certain others. So, a group that might have stabilized into several non-communicative groups, under influence, is more often breaking these group boundaries by the gradual co-optation process made possible through influence.

Furthermore, we see that influence is sensitive to increasing contrast. This is not surprising since under influence in general, the group will tend to interact for a much longer period of time; compare (“None” and “I__”). This is due to the fact that under non-influence, once all of the members of a group take all of the characteristics, the group has reached equilibrium; alteration of characteristics through balance does not count for the definition of stability since they represent secondary exchanges. Hence, we simply do not see the effect of contrast under the no-influence/no-balance condition since there is not enough time for contrast to be effective. When contrast is effective, we see that individuals tend to be less interactive with the group and are probably engaged with a few certain individuals, as contrast predicts. This obviously hinders stability.

The effect of contrast is attenuated under balance and influence (levels “IB__” to “IBC2”). Balance forces individuals to consider others outside of their dyadic relationships. Hence, exchanges of characteristics occur more frequently and time to stability is reduced.

HOMOGENEITY

We now look at the degree to which individuals are homogenous at the time of stability. Homogeneity is defined as the number of characteristics found in the individuals divided by the potential number of characteristics. For mutually exclusive characteristics, if two individuals hold opposing characteristics, they cancel each other out and add zero to the homogeneity count. The situations in which everyone is holding none of the characteristics and there are two groups, each holding characteristics opposite from the other group yield a homogeneity score 0.00. So the homogeneity score is descriptive of how close the group is to being whole, as it should be.

Table 3a. Regression on Homogeneity

Predictor	Coef	StDev	T	P	
Constant	0.92408	0.01065	86.74	0.000	
N	-0.0025132	0.0001610	-15.61	0.000	
K	0.0147348	0.0005389	27.34	0.000	
M	0.003429	0.001609	2.13	0.033	
C	0.044465	0.005338	8.33	0.000	
W	-0.074172	0.003219	-23.04	0.000	
B	-0.122553	0.005877	-20.85	0.000	
P	0.0016774	0.0001618	10.37	0.000	
X	-0.00568378	0.00003971	-143.14	0.000	
I	0.387971	0.006627	58.54	0.000	
CB	0.157094	0.007198	21.83	0.000	
BI	-0.037695	0.009292	-4.06	0.000	
CI	-0.140554	0.008047	-17.47	0.000	
BCI	-0.08472	0.01138	-7.44	0.000	
S = 0.1673		R-Sq = 64.7%		R-Sq(adj) = 64.7%	
Source	DF	SS	MS	F	P
Regression	13	829.343	63.796	2280.37	0.000
Error	16186	452.819	0.028		
Total	16199	1282.162			

First of all, we see that contrast promotes homogeneity, as predicted earlier, though the effect is not as strong as those of the other parameters; sub-groups are less likely to persist when the initial groups are initially heterogeneous.

The most significant effect comes from the increasing of the percentage of characteristics that are mutually exclusive (X). Clearly, having more ways in which individuals can sharply disagree will induce them to remain at odds. The next significant effect appears to be influence. As we saw influence increasing time to stability, here we see it increases the degree of homogeneity measured at the time of stability supporting the hypothesis that influence serves to break down group barriers. Since the influence variable is included in other interaction terms,

the interpretation of the coefficient is uncertain. However, a t-test shows us that the main effect is significant ($t = 25.53$). The extra time gives individuals chances to resolve differences.

Table 3b. Analysis of Variance for Homogeneity

				Individual 95% CIs For Mean Based on Pooled StDev					
IBCW	N	Mean	StDev	-+-----+-----+-----+-----					
None	1620	0.7340	0.2727						
_C1	1620	0.7393	0.2649						(*)
_C2	1620	0.7437	0.2618						(*)
_B	1620	0.6116	0.3377	(*)					
_BC1	1620	0.7547	0.2986						(*)
_BC2	1620	0.7972	0.2766						(* -)
I	1080	0.9873	0.0824						(* -)
I_C1	1080	0.9540	0.1175						(* -)
I_C2	1080	0.7543	0.2210						(*)
IB	1080	0.8272	0.2099						(*)
IBC1	1080	0.8876	0.2451						(*)
IBC2	1080	0.6452	0.3435	(-*)					
				-+-----+-----+-----+-----					
Pooled StDev =	0.2622			0.60	0.72	0.84	0.96		

As found earlier, balance is shown to decrease homogeneity and hence increase the time to stability (levels “None” vs. “_B_”) while influence sharply increases homogeneity (“None” vs. “I_”). We see that influence tends to be the dominant effect when both are present (“None” vs. “IB_”); the mean for “IB_” is greater than that for the no effect condition (“None”). As we saw from the regression model, contrast interacts positively with balance and negatively with influence. The additive interaction between contrast and balance seems reasonable. Contrast in this case will induce the positive type of balance or dissonance reduction. Individuals strongly tied through contrast will be more willing to accept a third party rather than relinquish the relationship. The interactive effects from influence and contrast (“I_” to “I_C2”) seem similar to those on time to stability. Since the time is increased, the effect of contrast becomes more prevalent. Without balance, sub-groups of individuals will remain closed off to others. There is very little probability that an outsider interacting with one of these will be accepted by the rest despite influence. As such, we should see the number of distinct groups to increase under the same interaction. These interactions correspond to those of time to stability, with the effects reversed: contrast/balance reduces time while contrast/influence increases time.

SUB-GROUP FORMATION

Under the conditions in which some of the traits/characteristics are mutually exclusive, it is possible for individuals to maintain values different from other members and never waiver. This is obviously applicable to the non-influence situation. So, we now examine the factors that determine the number of groups that emerge at the time of stability or at the time limit, round 999. The minimum number of groups is 1.

Table 4a. Regression on Log10(Number of Sub-Groups)

Predictor	Coef	StDev	T	P	
Constant	-0.19794	0.01538	-12.87	0.000	
N	0.0087691	0.0002325	37.72	0.000	
K	0.0163761	0.0007782	21.04	0.000	
M	-0.015089	0.002324	-6.49	0.000	
C	-0.081395	0.007708	-10.56	0.000	
W	0.140622	0.004648	30.25	0.000	
B	0.021281	0.008486	2.51	0.012	
P	-0.0012881	0.0002336	-5.51	0.000	
X	0.00634625	0.00005734	110.68	0.000	
I	-0.635432	0.009569	-66.40	0.000	
CB	-0.09644	0.01039	-9.28	0.000	
BI	0.21683	0.01342	16.16	0.000	
CI	0.29149	0.01162	25.08	0.000	
BCI	-0.11972	0.01643	-7.29	0.000	
S = 0.2415		R-Sq = 58.3%		R-Sq(adj) = 58.3%	
Source	DF	SS	MS	F	P
Regression	13	1320.04	101.54	1740.77	0.000
Error	16186	944.15	0.06		
Total	16199	2264.19			

Homogeneity and number of groups are negatively correlated ($r = -0.573$). Hence, it is not surprising to see that the variables that strongly impact homogeneity, affects the sub-group count as well. We saw that mutually exclusive traits (X) decrease homogeneity and hence here we see it increase the number of disparate groups. Influence here serves to reduce the number of groups as it increases homogeneity.

Table 4b. Analysis of Variance for Sub-Groups

				Individual 95% CIs For Mean Based on Pooled StDev			
IBCW	N	Mean	StDev	-+-----+-----+-----+-----			
None	1620	0.4970	0.4223				(*)
__C1	1620	0.4891	0.4160				(*)
__C2	1620	0.4825	0.4085				(*)
B	1620	0.5181	0.3451				(-*)
_BC1	1620	0.4236	0.3549				(*)
_BC2	1620	0.3978	0.3295				(-*)
I_	1080	0.0108	0.0581	(-*)			
I_C1	1080	0.0950	0.1862		(*-)		
I_C2	1080	0.4875	0.3206				(-*)
IB_	1080	0.2488	0.1838			(-*)	
IBC1	1080	0.1332	0.1917			(*)	
IBC2	1080	0.4930	0.4151				(*)
				-+-----+-----+-----+-----			
Pooled StDev =	0.3358			0.00	0.15	0.30	0.45

We find that the effects here are similar to those of homogeneity but in the opposite direction as predicted by the negative correlation. Contrast here increases the sub-group count under influence while it decreases the sub-group count when combined with balance. As with homogeneity, we find that the balance only and the influence/balance/strongest-contrast (“IBC2”) condition have a strong tendency to produce splintered groups.

POSITIVE TYPE BALANCE

So far, we have found evidence for positive balance occurring under conditions of contrast while negative balance occurring otherwise. We can directly measure whether one type occurs more often than the other type and when. Here, we regress the difference between the number of characteristics gained through positive type dissonance reduction and the number of characteristics that were relinquished or dropped as part of negative dissonance reduction on the parameters.

Table 5a. Regression on Log10(Trait Gains – Trait Losss)

Predictor	Coef	StDev	T	P
Constant	0.17161	0.09773	1.76	0.079
N	-0.026330	0.001536	-17.14	0.000
K	0.003658	0.005142	0.71	0.477
M	-0.32792	0.01535	-21.36	0.000
C	1.05606	0.03761	28.08	0.000
W	-0.26828	0.03071	-8.74	0.000
P	0.011018	0.001534	7.18	0.000
X	-0.0293375	0.0003788	-77.44	0.000
I	1.14863	0.04508	25.48	0.000
CI	0.06092	0.05428	1.12	0.262

S = 1.128	R-Sq = 54.8%	R-Sq(adj) = 54.7%			
Source	DF	SS	MS	F	P
Regression	9	12479.3	1386.6	1089.35	0.000
Error	8090	10297.4	1.3		
Total	8099	22776.7			

We see that by far the strongest predictor is the percentage of mutually exclusive ties. Having more of these induces individuals to reduce dissonance by distancing themselves from others. This should not be surprising considering, under that a difference between mutually exclusive traits is counted double over a difference between an attitude or trait and its non-existence.

Also, our earlier findings have been verified. Both contrast and influence induce the positive type of dissonance reduction.

RECIPROCITY

We now address the formation of reciprocal ties. How do contrast and dissonance influence the formation of reciprocal ties and how do they interact with influence? Given our dichotomized network of “strong” ties, we examine to degree to which they are reciprocal. Reciprocity is defined as the percentage of ties involved in a reciprocal dyad. However, this score alone is not meaningful unless we have a frame of reference. We use the random null-model as the basis of comparison; the reciprocity percentage is measured against the degree of reciprocity that one would find by chance in a network of equivalent size and density. So for each network, a random graph of equivalent size and density is generated and difference in reciprocity percentage is analyzed.

Table 6a. Regression on Reciprocity Difference from Chance

Predictor	Coef	StDev	T	P
Constant	0.05418	0.01057	5.13	0.000
N	-0.0018991	0.0001597	-11.89	0.000
K	-0.0138943	0.0005347	-25.99	0.000
M	0.030553	0.001597	19.13	0.000
C	0.010054	0.005296	1.90	0.058
W	0.077788	0.003194	24.36	0.000
B	0.295475	0.005831	50.67	0.000
P	-0.0024706	0.0001605	-15.39	0.000
X	0.00253253	0.00003940	64.28	0.000
I	-0.081741	0.006575	-12.43	0.000
CH	-0.229094	0.007142	-32.08	0.000
HI	-0.102516	0.009220	-11.12	0.000
CI	0.095945	0.007984	12.02	0.000
CHI	0.02886	0.01129	2.56	0.011

Source	DF	SS	MS	F	P
Regression	13	308.525	23.733	861.73	0.000
Error	16186	445.774	0.028		
Total	16199	754.299			

We observe that exclusivity of characteristics drives reciprocity. Pairs of individuals are more likely to form when the basis of relationships tends to be on exclusive characteristics. Balance alone also appears to engender reciprocity. A straight t-test shows us that the significance of balance is assured ($t = 33.33$) and the direction is positive.

Table 6b. Analysis of Variance for Reciprocity Difference from Chance

BICW	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
None	1620	0.0263	0.1155	(*)
__C1	1620	0.0568	0.1389	(*)
__C2	1620	0.0932	0.1468	(*)
__I	1080	0.0076	0.1151	(*)
__IC1	1080	0.0388	0.1135	(*)
__IC2	1080	0.2664	0.1429	(-*)
B__	1620	0.3215	0.3284	(*)
B_C1	1620	0.1413	0.2197	(*)
B_C2	1620	0.1417	0.1953	(*)
BI__	1080	0.2004	0.2589	(*)
BIC1	1080	0.0913	0.1773	(*)
BIC2	1080	0.1989	0.2158	(*)

Pooled StDev = 0.1939

Note that the order for the levels are changed: instead of IBCW, here we have BICW.

We once again see that contrast serves to moderate balance. Hence while, balance is the main driving force behind reciprocity (“__” vs. “B__”), its effect is reversed under contrast (“B__” to “B_C2”). Furthermore, we can see that influence serves to moderate the effect of

balance (“B___” vs. “BI___”) while, it reverses the effect of contrast; under influence, contrast motivates reciprocity (“_I_” vs. “_IC1”). Here, we see contrast dominates and becomes conflated with influence to produce much higher rates of reciprocity. What can be inferred is that individuals who influence or become influenced by others form strong relationships; these individuals contrast with others thus giving them motivation to maintain the tie. However, influence alone reduces reciprocity (“___” vs. “_I_”), again as it breaks inter-group boundaries.

WEAK TRIADS

Often, we are concerned with relationships other than the dyad. As balance predicts, the introduction of a third individual in the context of the dyad affects the dynamics and can potentially change the relations as the literature predicts (Simmel, 1950). Hence, we consider the kinds of relationships that can form involving three individuals. We expect balance to drive both transitive and weak triads. The first structure we examine is the weak triad. As with reciprocity, we are interested in the degree to which the virtual groups differ in triad count from randomly generated networks. Furthermore, the measure is a count of directed ties involved in a triad rather than distinct triads themselves. Whenever a set of relations connecting three people is found, the tally is increased. Hence, three people having reciprocal relations between one another count as six weak triads. A transitive set of ties, with one of the relations being reciprocal, counts as two weak triads.

Table 7a. Regression on Log10((Weak Triad Difference from Chance))

Predictor	Coef	StDev	T	P	
Constant	0.34068	0.04217	8.08	0.000	
N	0.0449094	0.0006372	70.48	0.000	
K	0.058204	0.002133	27.29	0.000	
M	0.012423	0.006370	1.95	0.051	
C	-0.02038	0.02113	-0.96	0.335	
W	0.09878	0.01274	7.75	0.000	
B	0.48629	0.02326	20.91	0.000	
P	-0.0075982	0.0006402	-11.87	0.000	
X	-0.0006822	0.0001572	-4.34	0.000	
I	0.53979	0.02623	20.58	0.000	
CB	-0.21935	0.02849	-7.70	0.000	
BI	-0.41498	0.03678	-11.28	0.000	
CI	0.29230	0.03185	9.18	0.000	
CBI	-0.07685	0.04504	-1.71	0.088	
S = 0.6620		R-Sq = 36.2%	R-Sq(adj) = 36.1%		
Source	DF	SS	MS	F	P
Regression	13	4024.42	309.57	706.40	0.000
Error	16186	7093.31	0.44		

Total 16199 11117.74

The most significant predictors are size and characteristics. This finding is not quite intuitive. With larger groups, there will be more triads, obviously. This is assisted by a higher degree of initial differentiation (K). So, while the variance in the difference count should increase, the mean difference should remain constant but it does not. This implies that there is an underlying dynamic not associated with balance, influence, or contrast which subtly produces network structures over and above what one would expect from random chance.

Also, we find that both balance and influence drive the formation of these triads, while the effect of contrast is conflated with the two dominant effects. These interactions are clearly seen below.

Table 7b. Analysis of Variance for Log10(Weak Triad Difference from Chance)

IBCW	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev		
None	1620	1.5641	0.7413	(*)		
_C1	1620	1.5936	0.7211	(*)		
_C2	1620	1.5912	0.7041	(*)		
_B	1620	2.0495	0.7476		(*-)	
_BC1	1620	1.8615	0.8764	(*)		
_BC2	1620	1.8580	0.9202	(*)		
I	1080	2.1019	0.7030		(*-)	
I_C1	1080	2.2661	0.6910		(-*)	
I_C2	1080	2.5808	0.7700		(--*)	
IB	1080	2.1725	0.7310		(*-)	
IBC1	1080	2.1020	0.7486		(*-)	
IBC2	1080	2.2939	0.8216		(*-)	
Pooled StDev =		0.7721		1.80	2.10	2.40

As we saw in the regression, we see here that influence is the overall dominant driver behind the formation of weak triads (“None” to “_BC2” vs. “I__” to “IBC2”). However, its singular effect is not that much greater than that of the singular effect of balance, which we expect to also be a determinant of triads; by comparing the levels “_B__” (balance only) and “I__” (influence only) we see that their effects are similar. In level “IB__” (both balance and influence), we see that their effects are slightly additive. The introduction of contrast, however, changes the interactions. From levels “I__” to “I_C2”, we see that influence and contrast interact positively while, from levels “_B__” to “_BC2”, we see that balance and contrast interact negatively. Levels “IB__” to “IBC2” appear to average these two interactive effects.

With the exception of the contrast only and influence only, these findings parallel those from the analysis of reciprocity.

TRANSITIVE TRIADS

In the literature, a specific kind of weak triad is one composed of transitive ties. If individual A has a tie to individual B and B to C, then the triad is made transitive when A has a tie to C. $A \rightarrow B$ and $B \rightarrow C$ implies $A \rightarrow C$. Again, we are interested in how contrast, dissonance, and influence affect the generation of these triads such that the degree of their occurrence departs from the random null-model. We hypothesize that balance should have the dominant effect.

Table 8a. Regression on Log10(Transitive Triad Difference from Chance)

Predictor	Coef	StDev	T	P	
Constant	-0.89528	0.09307	-9.62	0.000	
N	0.032234	0.001406	22.92	0.000	
K	-0.075336	0.004708	-16.00	0.000	
M	0.13672	0.01406	9.72	0.000	
C	-0.09174	0.04663	-1.97	0.049	
W	0.48592	0.02812	17.28	0.000	
B	1.74523	0.05134	33.99	0.000	
P	-0.011557	0.001413	-8.18	0.000	
X	0.0103542	0.0003469	29.85	0.000	
I	-0.40396	0.05789	-6.98	0.000	
CB	-1.08870	0.06288	-17.31	0.000	
BI	0.02134	0.08117	0.26	0.793	
CI	0.76703	0.07030	10.91	0.000	
CBI	-0.60899	0.09942	-6.13	0.000	
S = 1.461		R-Sq = 23.1%		R-Sq(adj) = 23.0%	
Source	DF	SS	MS	F	P
Regression	13	10380.65	798.51	374.02	0.000
Error	16186	34556.13	2.13		
Total	16199	44936.78			

As expected, balance is the primary motivator of transitivity. Specifically, positive balance reinforces the emergence of this structure. Furthermore, we see that exclusivity of characteristics promotes transitivity as well.

Table 8b. Analysis of Variance for Log10(Transitive Triad Difference from Chance)

				Individual 95% CIs For Mean Based on Pooled StDev		
BICW	N	Mean	StDev	-----+-----+-----+-----		
None	1620	-0.250	1.115	(*)		
_C1	1620	-0.175	1.123	(*)		
_C2	1620	-0.024	1.133	(-*)		
I	1080	-0.393	1.626	(*-)		
_IC1	1080	-0.328	1.796	(-*)		
_IC2	1080	1.379	1.523	(-*-)		
B_	1620	1.494	1.549	(*)		
B_C1	1620	0.574	1.690	(-*)		
B_C2	1620	0.541	1.551	(*)		
BI_	1080	1.372	1.621	(-*)		
BIC1	1080	0.317	1.830	(*-)		
BIC2	1080	0.870	1.937	(*-)		
Pooled StDev = 1.529				-----+-----+-----+-----		
				0.00	0.60	1.20

Again, note that the order for the levels are changed: instead of IBCW, here we have BICW.

We confirm that balance has the dominant effect (“None” to “_IC2” vs “B_” to “BIC2”). Furthermore, influence and contrast interact additively under no balance (“_I_” to “_IC2”) while contrast and balance interact antagonistically (“B_” to “B_C2”). The impact of influence, with the exception of its interaction with contrast, is either nil or negative. Why should influence interact so inconsistently with the other two effects? Without balance, influence is the only mechanism capable of breaking apart strong reciprocal dyads formed through contrast. Therefore, it is likely that under influence and contrast, two individuals tightly bound will elect a same third member to form a transitive relation. We see that a similar dynamic occurs in the contrast only conditions (“None” to “_C2”) though to a far lesser degree. However, balance acts cross-purposively to contrast and influence. What we can infer is that there is only room for one or two effects to drive transitivity. Balance, being strongly dominant, is merely hindered by contrast and influence rather than supplemented. These effects are very similar to those found in the analysis of reciprocity.

STRONG TRIADS

We now examine the triads of individuals joined by reciprocal ties. These ties reflect mutual, positive relationships of high interaction, and hence, strong philos or affect. We can consider these as Simmelian ties (Krackhardt, 1996)(Simmel, 1950).

We see that the strongest weight of contrast in conjunction with influence (i.e. level “_IC2”) most strongly drives strong triad formation. Since contrast has been shown to increase reciprocity, we can confirm that this interaction is in fact producing triads with reciprocal ties. Looking at levels “None” to “_C2”, we see that contrast alone has little effect. Since influence tends to act as a diversifying agent, here, it allows for individuals involved in reciprocal dyads to extend their relations beyond the pair and include a third (“_I_” to “_IC2”). As with transitivity, contrast negates the effect of balance (“B_” to “B_C2”).

COMPARISON TO EMPIRICAL DATA

We examine how well the models behavior compare to real social network data. We use the data from the Newcomb acquaintanceship study (Newcomb, 1968)(UCINET). Newcomb obtained preference rankings between 17 men placed in a single dormitory at the University of Michigan in 1956. We use the measures of reciprocity and all three triads from the final, week 15, network. The final network is used as opposed to any of the ones from the earlier time points as it represents the most stable preference or attraction ratings. In transforming the ranking matrix, to a dichotomous interaction matrix, we translate the top-half of the ranks into 1’s and the bottom half into 0’s.

We attempt to determine which of the models minimize the absolute differences in the aforementioned measures between those of the empirical network and the ones produced by the models. In order to maintain consistency, we use ranked interaction, as a proxy for preference/attraction, from the model instead of the raw interaction history. We fix the number of individuals for each of the models (i.e. 17) while varying all of the other parameters. Some of the experimental conditions do not allow for the same of ties found in the empirical network; under some conditions, not all individuals have a chance to interact with one another. Hence, we must control for the total number of ties in the following analyses. Hence, the analyses of variance are performed on the residuals obtained from regressing the absolute differences on total ties. The question we ask is, accounting for the effect of the number ties on the differences in the measures, are there any effects left that the models can systematically explain. We find often that the answer is yes. What we seek from comparisons are the models whose residuals are systematically negative; their accuracy is better than what is predicted by ties alone.

Finally, we stress that what we are performing is an indirect validation test. A more comprehensive test would involve other parameters to be constrained in the initial condition; in our case we only fix the size of the group (i.e. N). However, data on the number of traits and the individuals who carried those traits are not readily available as well as any indication of how frequent individuals were capable of interacting, which parallels the mode of interaction parameter, M . Instead, we vary the parameters, that we cannot obtain from data, across a limited range to see to which of the focal dynamics constitute the best model.

Table 10a. Analysis of Variance of Residuals of Absolute Reciprocity Difference from Empirical Controlling for Total Ties

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
None	540	0.0273	0.0851	(-----*-----)
__C	1080	-0.0174	0.0969	(--*--)
B	540	0.0107	0.1239	(----*----)
_BC	1080	0.0159	0.1191	(--*--)
I__	360	0.0061	0.0696	(----*----)
I_C	720	-0.0231	0.0795	(--*--)
IB_	360	-0.0137	0.1064	(----*----)
IBC	720	0.0006	0.1090	(--*--)
Pooled StDev = 0.1024				-----+-----+-----+-----+-----+
Reciprocity score of empirical network: 0.588237				-0.020 0.000 0.020 0.040

We ignore the weight of contrast parameter and average it into C in order to allow for more interpretable results. Controlling for the total number of ties we observe that the ‘I_C’ model, which is influence/contrast, does the best in minimizing the differences between the reciprocity score obtained from the Newcomb data, 0.588 and the ones produced from the model. This is followed by the contrast only model. These results should not surprise us since contrast happens to be a strong motivator of reciprocity; individuals that share traits that contrast with the rest are likely to interact quite frequently. It is interesting to note that the difference scores from combined model, “IBC”, are almost completely explained by the number of ties produced by that model while “IB_” model performs similarly to “I_C”. This suggests that the contrast and balance are not synergistic, but rather competitive. We observe that the worst model is the one in which none of the mechanisms are enabled; we can conclude that some kind of mechanism is present during interaction that constrains the degree of observed reciprocity. Finally, the models devoid of influence over-predict the level of reciprocity, with the exception of the contrast-only

model suggesting that influence is crucial in constraining interactions such that the dichotomization produces a more accurate count of reciprocal ties.

Table 10b. Analysis of Variance for Residuals of Absolute Reciprocity Difference from Empirical

Level	N	Mean	StDev	-----+-----+-----+-----+-----			
0.000	1080	0.0351	0.0823				(--*--)
33.333	720	0.0013	0.0922		(---*---)		
44.444	720	-0.0139	0.0798	(---*---)			
50.000	720	-0.0169	0.0866	(---*---)			
88.889	720	0.0041	0.1232		(---*---)		
100.000	1440	-0.0136	0.1231	(-*--)			
Pooled StDev = 0.1020				-0.020	0.000	0.020	0.040

We also find a mutually exclusive characteristics proportion of ~50% seems to produce the most similar reciprocity score. This suggests that individuals base similarity on both exclusive and independent characteristics. However, the pattern is clearly non-linear; when all of the characteristics are mutually-exclusive, the difference approaches that obtained when only half are mutually-exclusive.

Table 10c. Analysis of Variance for Residuals of Log10(Abs. Weak Triads Difference from Empirical)

Level	N	Mean	StDev	-----+-----+-----+-----+-----			
None	540	0.0193	0.2121				(---*---)
__C	1080	0.0378	0.1712				(-*--)
__B	540	-0.0692	0.3125	(---*---)			
__BC	1080	0.0267	0.3157				(---*---)
I__	360	-0.0128	0.3458		(----*----)		
I_C	720	0.0422	0.4109				(---*---)
IB__	360	-0.1466	0.3923	(----*----)			
IBC	720	-0.0217	0.3921				(---*---)
Pooled StDev = 0.3183				-0.140	-0.070	-0.000	0.070
Weak Triads in Empirical Network: 1506							

We find that the “IB_” or the influence/balance model does best in predicting the number of weak triads that emerge from the interactions. When we consider this along with the observation that balance alone does second best, we can conclude that the balance mechanism is dominant in predicting the formation of weak triads. This finding is not altogether surprising as balance can operate as a triad forming dynamic. Furthermore, we observe again that the

differences from combined model, influence/balance/contrast are mostly predicted by the number of ties alone and performs similarly to the influence only (i.e. “I__”) model; the effects appear to cancel each other.

Table 10d. Analysis of Variance for Residuals of Log10(Abs. Transitive Triads Difference)

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
None	540	0.0643	0.1200	(---*---)
__C	1080	0.0604	0.1194	(-*---)
B	540	-0.0767	0.3124	(--*---)
_BC	1080	0.0133	0.2829	(-*---)
I__	360	0.0177	0.2881	(---*---)
I_C	720	-0.0203	0.2437	(--*---)
IB_	360	-0.0900	0.3336	(---*---)
IBC	720	-0.0447	0.3240	(---*---)

Pooled StDev = 0.2548
Transitive Triads in Empirical Network: 638

For transitivity, we see a similar pattern in which balance is primary motivator of network structure. However, one difference here is that the combined model, this time, does third best. The differences, produced by this model, cannot be explained by the number of ties alone. For transitive ties, the contrast only moderately competes with balance, but contrast by itself is not better than the default model in predicting.

Table 10e. Analysis of Variance for Residuals of Log10(Absolute Strong Triads Difference)

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
None	540	0.0656	0.0421	(--*---)
__C	1080	0.0594	0.0389	(-*---)
B	540	-0.0375	0.3758	(--*---)
_BC	1080	0.0145	0.2785	(-*---)
I__	360	0.0587	0.0838	(---*---)
I_C	720	-0.1460	0.3110	(-*---)
IB_	360	-0.0579	0.3258	(---*---)
IBC	720	0.0137	0.2439	(--*---)

Pooled StDev = 0.2418
Strong Triads in Empirical Network: 37

A strong triad combines the notions of the triad and reciprocity; it seems that both mechanisms must play a role in the formation of this structure. However, we see that the contrast mechanism, combined with influence, does best in predicting the number of strong

triads. Not surprisingly, the second and third best models are the balance models. Finally, we again see that the combined model produces network structures that are explained largely by raw density.

CENTRALIZATION

Centralization is a network measure descriptive of the extent to which a network resembles a star shape; individuals have ties with only one individual in the center of it all. Thus, a centralized network can be regarded as being composed of special dyads. More formally, centralization is computed as follows:

$$Centralization_Index = \frac{\sum_i^n [C_{max} - C_i]}{n(n-1)}$$

C_{max} is the largest number of observed ties going to one individual. The $n(n-1)$ represent the theoretical maximum value the numerator can take on (i.e. in a star network). Hence, the index lies in the interval [0.0, 1.0]. A star network will have a centralization of 1.0. However, the distribution of this value varies depending on the size and density of the network. Thus, we employ a similar non-parametric procedure as we did for determining the significance of reciprocity and triads. For each generated network, we generate a random graph of equivalent size and density and note its centralization score. The following analysis focuses on the difference between the centralization of the model evolved network and a randomly generated one.

Table 11a. Regression on Log10(Centralization Difference from Chance)

Predictor	Coef	StDev	T	P
Constant	-0.012882	0.002704	-4.76	0.000
N	0.00063907	0.00004085	15.64	0.000
K	-0.0000400	0.0001368	-0.29	0.770
M	0.0069950	0.0004084	17.13	0.000
C	0.000797	0.001355	0.59	0.556
W	-0.0066178	0.0008169	-8.10	0.000
B	0.013988	0.001491	9.38	0.000
P	-0.00005910	0.00004105	-1.44	0.150
X	-0.00007059	0.00001008	-7.01	0.000
I	-0.001564	0.001682	-0.93	0.353
CB	-0.015099	0.001827	-8.27	0.000
BI	-0.001122	0.002358	-0.48	0.634
CI	-0.008364	0.002042	-4.10	0.000
CBI	0.004532	0.002888	1.57	0.117

S = 0.04244	R-Sq = 7.2%	R-Sq(adj) = 7.1%			
Source	DF	SS	MS	F	P
Regression	13	2.26179	0.17398	96.58	0.000
Error	16186	29.15957	0.00180		
Total	16199	31.42136			

We must keep in mind that this model does not fit as well as the other ones given the low adjusted R^2 . Size and mode of interaction are the strongest determinants of centralization. Network measures such as centralization are sensitive to the size and density hence these effects are not immensely surprising. What is surprising is that they represent the strongest effects suggesting that the effects, contrast, balance, and influence are secondary.

Table 11b. Analysis of Variance for Log10(Centralization Difference from Chance)

				Individual 95% CIs For Mean Based on Pooled StDev				
IBCW	N	Mean	StDev	-----+-----+-----+-----+-----				
1	1620	-0.00551	0.04343					
_C1	1620	-0.00835	0.04006					
_C2	1620	-0.00771	0.04293					
_B	1620	0.00847	0.04355					(--*)
_BC1	1620	-0.00775	0.04133					(-*)
_BC2	1620	-0.01053	0.04120					(-*)
I	1080	-0.00861	0.04312					(-*)
I_C1	1080	-0.01214	0.04562					(-*)
I_C2	1080	-0.02682	0.04473					(-*)
IB	1080	0.00425	0.04218					(--*)
IBC1	1080	-0.00960	0.04340					(-*)
IBC2	1080	-0.02477	0.04823					(-*)
Pooled StDev = 0.04312				-----+-----+-----+-----+-----				
				-0.024	-0.012	-0.000	0.012	

Contrast (t = -17.18) and influence (t = 10.96) both decrease centralization while balance increases centralization (t = 6.77), though the effect is not as significant. Furthermore, we see that contrast interacts negatively with both influence and balance. This is a statement on the effect of these dynamics on the distribution of ties. Contrast, only in conjunction with influence and/or balance will result in evenly distributed strong ties in strong triads. Hence, the centralization measure will be quite low.

CONCLUSIONS

The following table summarizes the findings:

	Time	Homo	SubGr	Balanc	Recipr	WkTri	TnsTri	StrTr	Cent.
C	0	0	0	+	+	0	+	0	0
I	+	++	--	+	-	+	++	++	+
B	+	-	+	n/a	++	+	++	++	+
CB	+	+	-	n/a	-	-	--	-	-
CI	+	--	++	0	++	+	++	++	-
BI	-	+	-	n/a	+	+	++	+	+
CBI	0	?	?	?	?	?	?	?	-
X	0	-	+	-	+	0	+	+	0

0 is no or very little effect. + is some relative positive effect. ++ is a very strong positive effect.

- is a negative effect. -- very a strong negative effect. ? implies a non-linear interaction.

This summary is based on the ANOVA tables and not the regression coefficients. Hence, 'C' refers to the singular effect of contrast and not the effect of contrast average across all balance and influence conditions.

When individuals in a group interact and move towards a state of stability, they tend to interact with those with whom they are more similar. We have shown that the variable effects on interaction between individuals when their similarity perceptions are driven by contrast and dissonance reduction. Based on experimental data and sociological and decision-making theories, we believe individuals to behave according to both dynamics. Our model shows that these mechanisms have differential and interactive effects on the interaction behavior of groups and on the formation of ties and network structures. Accordingly, we have observed that contrast under influence induces more positive dissonance reduction. Given a sufficient level of differentiation in the initial population, an individual will seek to interact most with an individual with whom their similarities contrast sharply with many others. However, his assessment of similarity to the partner is also affected by how he regards the partner's associates. Under situations in which contrast-based similarity induces interaction, we believe that individuals will reduce dissonance by accepting the associates; the immediate relationship is strong enough. This

finding supports the empirical observation that individuals tend to make agreements (i.e. achieve balance) with high-attraction others (Newcomb, 1961).

We then find that contrast alone can drive the formation of reciprocal and transitive ties. However, balance alone has a greater effect that is matched only by the conjunction of contrast and influence. In the formation of both weak and strong triads, the singular effect of contrast is negligible. But, in the formation of strong triads, under influence, contrast plays a greater role than balance; both contribute to strong triads. The balance, balance/influence, and contrast/influence consistently promote reciprocity and triad formation while contrast/balance produce fewer structures. The first two even promote centralization. When all three conditions are in effect, the impact on structure formation is moderate relative to the strongest effect generated by contrast/influence. Even still, the scores significantly exceed that from what one would expect from the null-model.

When using the empirical Newcomb network as our basis of comparison, we are guided to the conclusion that contrast, influence, and balance contribute to different types of structures. Reciprocity can be driven by either contrast or balance, each in conjunction with influence. That is, the number of dyads that match the data requires influence and one other dynamic. Not surprisingly, the formation of transitive and weak triads is largely driven by balance. Both the balance/influence and the balance only models are better in predicting the frequency of these structures as expected by the theory. However, for strong triads, it is the contrast/influence that is the best predicting model while the balance and balance/influence are the second and third best. This suggests that under the assumptions of these models, strong dyadic interactions are the primary or initial motivators of strong triads, and balanced interactions secondary; it just as easily could have been the other way around. This implies that positive balance is induced by contrast hence the formation of the triad. Finally, we observe that the synergistic models, contrast/balance/influence and contrast/balance, tends to produce frequencies of structures that are largely explained by the number ties present in the network. This finding is not altogether surprising since the combined dynamics seemed to produce similar effects when compared to a null-model. Since we have already seen each of the dynamic producing some kind of significant effect, whether good or bad, we can infer that the dynamics somehow manage to negate one another. Since we know that triads and reciprocity do occur in real networks and we have also seen evidence of contrast and balance, we are inclined to conclude that contrast and balance

often do not operate simultaneously. The relationship formation process involves multiple dynamics each occurring at different points in time. While it is impossible to track when and how specific mechanisms contribute to the formation of ties, the models show that contrast and balance cannot both be in effect constantly. Similarly, it is difficult to consider the conditions that have no influence as valid ones. Influence is a dynamic that is ever-present. Unless we focus on a particular context in which it is not, we might want to direct our attention on the models that contain influence.

Also, we find that contrast and balance interact antagonistically in predicting centralization. Greater levels of centralization are found in balance and balance/influence networks. Though we have not done so here, we can easily use the empirical networks in comparing the centralization scores.

While the research focuses on the effects of contrast and dissonance on relationship formation, it is clear that the type of relevant characteristics plays a significant role. The salience of mutually exclusive attributes cannot be ignored. Furthermore, we find that it is necessary for individuals to be able to influence one another in order for the network structures, that we observe empirically, to emerge from the model.

DISCUSSION

The emergence of reciprocal ties and triads under contrast and balance is not an obvious dynamic considering that the compositions of the original groups are randomly generated. One can think imagine slight perturbations in the initial conditions (i.e. initially perceived similarities) will steer the dynamics of interaction. Under the model's assumptions, first impressions do matter. Furthermore, the process quickly reinforces itself and promotes reciprocity. Similarity between two individuals induced by contrast with others is further enhanced when characteristics are exchanged during interaction giving rise to a stronger bond, especially if they are unique to that dyad.

We observe that the initial compositions of real-life groups are usually not as differentiated as complete noise. Therefore, any structure that emerges from this model that makes no such assumption ought to be somewhat surprising. However, we do regard the assumptions underlying contrast, balance, and influence to be quite reasonable. Our findings suggest that these mechanisms play a large role in the determination of homophilous ties,

especially in groups shifting from being highly differentiated to completely stable. The literature predicts that initial size and differentiation do matter in the formation of relationships; specifically, more inter-group relationships will be found given higher levels of size and differentiation (Blau, 1977). This hypothesis is moderately supported by the model. In the analysis of sub-groups, we see that both group and number of characteristics promote higher levels of final differentiation while, the homogeneity regression reveals homogeneity promotes overall homogeneity. The theory is especially well supported when we consider the initially, differentiated large groups which never stabilize and remain, however, somewhat homogenized. The literature also predicts that homogenous sub-groups impede macro-social integration. In the model, both contrast and balance induce the formation of at least triadic groups; larger group structures can be sought, if they have emerged.

Differentiation is also related to the complexity of the social structure, and this, too, is supported in the model. Higher levels of the characteristic size (K) predict more weak triads while predicting fewer reciprocal ties, and transitive and strong triads; that is, it predicts more of the less well-defined structure and less of the tightly defined structures.

However, the theoretical implications of the model do not cover specific kinds of differentiation such as those based on inequality or status differences. While the model is capable of simulating a fixed attribute vector, representing relatively immutable traits such as physical characteristics or status, the impact of the feature has yet to be analyzed. Research has shown that physical traits are often the bases of homophilous ties. One can argue that in evolving groups, such bases for similarity are diluted over time with increased communication and familiarity between individuals; the model captures this by the decrease of differentiation over time. However, in certain realistic contexts, the salience of immutable traits, such as race, remain fixed; here the model falls short. Research also shows that often interaction is largely determined by proximity. For these analyses, proximity has been avoided but may be easily added. Also, one might argue that lock-stepped interaction is unrealistic. The observation that the three modes of interaction have confounding effects on the dependent variables suggests that applying alternative timing schemes should yield different results. Finally, the model does not permit dissimilarities to occur beyond the negative dissonance reduction mechanism. Realistically, ties are severed and affect is frequently reduced. However, since the purpose of the

current model is to examine the formation of ties within groups, which undergo increasing homogeneity, these dynamics are not necessarily pertinent.

Testing the predictions of the model remains somewhat problematic. While it is possible to match the measures obtained from real networks to those generated from the model, it is difficult to do the reverse. How does one control for influence or balance in a group of individuals freely interacting. The interaction itself would need to be constrained which would have other consequences. We can assume that influence and balance are present as shown by past studies and manipulate contrast. It is also difficult to induce the “important” characteristics on which similarities are based. How does one control for those that are mutually exclusive and those that are not. For this measure, it seems only possible to determine this from individuals ex-post and perform the first kind, comparison analysis.

Finally, what we have presented are specific implementations of the contrast, balance, and influence mechanisms. Clearly, one can argue for a host of other implementations to be equally valid. Until these dynamics have been adequately formalized, we can only strive to seek consistency in the broad conclusions obtained from these exercises which may vary in their specific implementations.

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