How Network Structure and Cultural Sentiments Shape Affective Alignment and Behavior Dynamics in Online Collaborative Task Groups

DARTMOUTH

Andrea Sedlacek

Honors Thesis

Dr. Kimberly Rogers, Advisor

Program in Quantitative Social Science

Dartmouth College

June 5, 2020

Acknowledgements

I want to acknowledge several people who have made this research project possible.

First, I am tremendously grateful for the support of my incredible advisor, Dr. Kimberly Rogers. Her mentorship empowered me to strive to explore and complete such challenging work. Professor Rogers has been an integral part of my experience with the Quantitative Social Science program and her passion and expertise have inspired me and guided me through this process. I would also like to thank the members of the THEMIS.COG project, particularly Jonathan Morgan, who helped further familiarize me with Python NetworkX and ggplot2 and was always willing to help me troubleshoot.

I am grateful for the James O. Freedman Presidential Scholars program which introduced me to Professor Rogers and the Social Interactions, Groups and Inequality Lab. My experience as a Presidential Scholar formed the base on which I could complete this honors thesis project. I want to thank Jun Zhao for her help and support as a Presidential Scholar.

I want to thank the QSS program, particularly Professor Wu and Professor Cooper, for their time and support as advisors to this year's QSS thesis students. I am grateful for their help in QSS 81 and in navigating this process throughout the year.

Lastly, I am extremely grateful for the support of my parents, sisters, and Brandt. Especially given the current situation in which I am living at home with them, I could not have completed this project without their support and encouragement.

Contents

List of Figures

List of Tables

Chapter 1 – Introduction

Given the increase of technology and work in online contexts, understanding the social forces behind self-organized collaboration is becoming increasingly important. Our society is what scholars have described as an emerging distributed economy and digital democracy (Townsend 2013, Blowfield & Johnson 2012, Bogers & West 2012, Helbing & Pournaras 2015). The collaborative development of software in online social coding communities like GitHub is a key example of these economic changes. GitHub is an open source software development platform designed for teams to host and review code, manage projects, and build software online. Currently, more than 2.9 million businesses and organizations use GitHub, including Google, Facebook, NASA, Bloomberg, SAP, and IBM (GitHub 2020). GitHub's membership base is growing exponentially, showing that work is moving in this direction. The creation of economic value and political problem solving is transitioning to this informal, online setting. A better understanding of online collaborative dynamics, the components and processes existent in any technology-mediated group interaction, is of increasing public and academic concern. The COVID-19 pandemic aggravates these changing dynamics as people are increasingly working online, making this topic even more relevant. By exploring group dynamics in open-source environments like GitHub, scholars can further understand the social and psychological mechanisms that drive human collaboration in the 21st century.

Collaborative dynamics guide hierarchy formation, interpersonal behavior, and affective experiences in group interactions (Bales 2000). In this thesis, I use simulations to analyze group interactions, collections of events that happen when individuals in a group react to stimuli generated by another group member. I investigate two dimensions of hierarchy, network structures and cultural meanings, to observe how the functional limitations of what a person can do (network structure) and what a person should do (cultural roles) impact the tension produced due to violated expectations and behaviors in groups. An illustrative example of the importance of this project is that software developers notoriously do not appreciate socio-emotive behavior. Linus Torvald, the inventor of Git (the software at the heart of

GitHub) is known for flippant attacks on the news and negative behavior (Cohen 2018). This negative behavior has led to constant turnover on his teams and many unhappy team members (Machkovech 2015). Linus is an example of how, for all of the amazing contributions that developers make, it is of increasing importance to understand the collaborative dynamics of teams in order to increase team productivity and retention. Though these group interactions take place online, people still need to manage the emotions of others.

Group dynamics can be studied through social ties between people. Network structure has been understood through the size of the network and structural connections. Simmel, an early sociologist and structural theorist, helped shape our understanding of small groups, which this project focuses on. Specifically, this thesis focuses on collectively oriented and task-oriented collaborative groups, as my research design was structured to match interaction methods for software development teams on GitHub. Previous literature has explored how structural power can be created through constraints in ties between people. Therefore, hierarchy can be shaped by the network structure. The collaborative task groups I observe follow the constraint of the group, meaning that the network dynamics are set within the group boundary. I operationalize network structure through two hierarchical structures from GitHub: an egalitarian network in which there is a level-playing field for all group members, and a hierarchical network in which only one member of the group can accept pull requests (requests to make changes to software on GitHub) and all other members have no power. Previous research has focused on the structural aspects of social networks and disregarded the cognitive-affective mechanisms that drive individuals' social behaviors and cause these network structures to evolve. In this study, I include cognitive- affective mechanisms and observe how structural hierarchies interact with cultural hierarchies.

To model group interactions with cultural factors, I use Affect Control Theory (ACT). ACT asserts that humans are motivated to maintain their affective alignment: they strive for their social experiences to maintain their interpretations of unfolding events and their fundamental beliefs about the social world and the roles of people involved (Robinson et al. 2006). People strive for coherence in their social experiences. Affective meaning is quantified through three abstract dimensions, referred to as EPA: evaluation (good vs. bad), potency (powerful vs. weak) and activity (lively vs. quiet) (Heise 2013). Cultural labels for identities and actions carry affective meaning and ACT relies on the idea that labelings evoke affect (Heise 2013). In interactions, people try to maintain affective or connotative meanings, rather than specific labels or denotative meanings (Robinson et al. 2006). Affective alignment is functionally equivalent to social coherence. Affective alignment impacts our behavior and emotions, the labels and interpretations we apply to ourselves and others in the situation, and even our interest or ability to stay in the group. Affective misalignment takes place when behaviors do not match expectations. Affective misalignment is measured as deflection in ACT. Deflection is the tension or feeling of uneasiness that arises when expectations are violated instead of met. I operationalize cultural meanings through the mathematically understandable identities of ACT using EPA values, which are defined as certain identity meanings according to the Interact and GitHub dictionaries. These dictionaries include identities with EPA values that were collected through empirical studies.

In this thesis, I explore how hierarchies of network structure and cultural meanings impact deflection, the tension of violated expectations, and behavior dynamics in groups. To observe behavior dynamics, I use Interaction Process Analysis, a framework from Bales that classifies behavior, act-by-act, as it occurs in small groups. Bales completed an extensive research study which has shaped our understanding of group process and which forms generalizations about efficient groups. I use ACT with Bale's model to inform the understanding of groups in my simulation model.

While previous work focuses on individual level factors, I combine a sociological approach which emphasizes the contextual effects based on group structure and composition with a computational approach to create a simulation model that is theoretically-grounded and readily scalable. Social simulation can be used to address previous gaps in literature by incorporating relevant theories and knowledge from psychology and sociology to implement behavior rules and decision-making algorithms in simulation. By utilizing ACT, I am able to produce naturally and socially appropriate artificially intelligent model agents that encompass both subtle and complex human social and affective skills (Hoey, Schroeder, and Alhothali 2013). The ability to simulate group interaction can provide insight into the social forces behind collaboration in a more comprehensive way.

I expand upon the work of THEMIS.COG (Theoretical and Empirical Modeling of Identity and Sentiments in Collaborative Groups), a collaboration between the University of Waterloo, Canada, The Potsdam University of Applied Sciences, Germany, and Dartmouth College, USA. GitHub, the world's largest software development platform, provides interaction data on thousands of open source software development projects (GitHub 2020). The THEMIS.COG project used data from repositories on GitHub to advance Group Simulator, a turn-based agent-based model that extends ACT to model group interactions (Heise 2013, Heise GS). Group Simulator predicts interaction dynamics and provides empirical validation of sociological theory, capitalizing on decades of sociological knowledge (Morgan et al. 2019). As the model has been validated using real data comparisons and predicting future developments, it can be used to make recommendations about how collaborations can be improved. These predictions have important implications for collaborative task groups, as they suggest which factors contribute to the success of task groups and which cause problems for group interaction.

My work uses Group Simulator to observe the effects of two dimensions of hierarchy, network structures and cultural meanings (status and power) associated with roles in the group. I observe how functional limitations interact to shape the deflection (tension produced by a groups' affective misalignment) and behavior dynamics produced in online collaborative task groups.

In Chapter 2, I will explore the literature that I bring to bear for this study. I will introduce the intellectual roots of ACT, the theoretical components of ACT, and social simulations based on ACT. I will review previous work on sentiment analysis, interaction process analysis, behavior in group dynamics, successful task groups, and online collaborations. In Chapter 3, I discuss my research design and the structure of my simulations in GroupSimulator, with emphasis on the network structures and cultural sentiments selected for this thesis. In Chapter 4, I share my results and insights into factors that predict the success of dynamics in online collaborations, and the factors that predict their disruption. In Chapter 5, I discuss my findings, the implications my findings have for task groups, and explore the limitations of my research design. Finally, I conclude and suggest avenues for future work.

Chapter 2 - Literature Review

As my research questions aim to explore how hierarchies of network structure and cultural sentiments impact the dynamics of online collaborative task groups, I explore literature that has shaped scholars' understanding of these two functional limitations. As this simulation study uses Affect Control Theory (ACT) with Bale's model of Interaction Process Analysis to inform the understanding of groups, the literature I review relates to collectively-oriented and task-oriented small groups.

I begin by exploring previous literature on network structure, both related to small groups and the creation of structural hierarchy. Next, I give a comprehensive overview of ACT, broken down into the intellectual roots of the theory, the theoretical components of ACT, and social simulation models based on ACT. I continue by exploring key analytical theories such as sentiment analysis, Interaction Process Analysis, and SYMLOG, in order to properly contextualize my findings of behavior dynamics. Next I share findings of previous group dynamics literature and factors former scholars have found to define successful task groups. I conclude this chapter by exploring the literature related to online collaborations and sharing how my work advances previous literature.

2.1 Network Structure

Sociologists have sought to understand group dynamics through the exploration of social relationships or networks created by social ties between people. Group dynamics can be studied both through the size of the network and the structural connections which exist within the network. I study literature on network structure within small groups as my research pertains to triads, groups of three people, and the three agent roles present in simulation: the actor, recipient, and observer. Simmel (1950) theorized about differences in group size, particularly the changes in the quality, dynamics, and stability of triads compared to dyads, groups of two. Though he theorized that key distinctions exist between dyads and triads, the movement from triads to larger groups only marginally impacts group dynamics (Simmel 1950). The expansion of the group does not impact the group dynamics in a substantial way as a member of the group is constrained by the norms of that clique, regardless of whether or not the clique is three or more people (Krackhardt 1999). This literature is particularly relevant to my work as I explore triads as a sample group form to gain insight into group dynamics that can be expanded to groups of larger sizes.

Network structure has been studied as a way to better understand the notion of structural power created by different configurations of actors and the flow of influence, information and authority (Coleman 1994). In a network structure in which A is connected with B, B is connected with C, and A and C are not connected, B is a very powerful actor (Simmel 1950). Ron Burt furthers the idea that being a bridging tie between others in a social system has distinct advantages with his structural holes theory (Burt 2002). Krackhardt also explored this idea by arguing that the quality of the tie determines the power of the tie: because B is bound by the necessity to satisfy norms with A and C, B is more constrained than A and C (Krackhardt 1999). Regardless of the structural power of actor B, this example shows how network structure can create a hierarchy within the group. Hierarchy is shaped and observed through constraints in ties between actors, as these constraints limit not only the passage of information and resources through the network, but also the attainment possible for particular actors within the network.

2.2 Intellectual Roots of the Theory

The overwhelming focus on the structural aspects of social networks in previous literature disregards the mechanistic angle of what drives individuals' social behaviors, such as the role of cultural sentiments (Squazzoni 2012). Findings in previous work support the necessity of exploring group dynamics beyond the lens of network structure. Identity is intertwined with network structure. "Collective intelligence" is predicted by flows of information between team members rather than by average or aggregate levels of individual intelligence (Woolley et al. 2010), as found in studies examining the relationship between team composition, communicative structures, and task performance (Katz et al. 2004). Miller found that a hierarchical structure can be created through a one-to-two triad differentiation in which one person is identified as distinct from the others (Miller 2007). Simmel theorized that as the number of slaves increases from one to two, the distinction between master and slave is heightened

(Simmel 1997). These findings are all rooted in identity differences between the actors in the group. Even in the context of software development, researchers found that gender and tenure diversity in an open source project directly impact the productivity of developers (Vasilescu et al. 2015). Developers make social inferences from their online contributions in GitHub (Dabbish et al. 2012, Marlow et al. 2013). There is insufficient understanding of how the unique identities and self-sentiments of the actors involved in interactions impact group dynamics.

Affect Control Theory enables further study of how sentiments impact collaboration. Like other symbolic interactionist theories (Mead 1938), ACT suggests that people process what happens in social interactions symbolically. Gestures (words or behaviors) operate as symbols by which people have shared meanings, giving people the capacity to anticipate how other actors are likely to respond to possible actions (Mead 1938). People act to maintain an equilibrium between symbolic meanings for actor identities, behaviors, and emotions and their interpretations of and responses to social events (Robinson et al. 1992).

2.3 Theoretical Components of ACT

The fundamental assumptions of ACT are that (1) cognitive understandings of social interactions around us cannot be separated from our affective reactions to them, (2) people act to maintain their affective meanings, and (3) emotions are signals about self-identity meanings in a situation and their alignment with fundamental self-conceptions (Robinson et al. 2006). This theory is corroborated by previous research which found that behaviors are not a function of just an individual's role, but also how occupants of that role are expected to behave in interactions with occupants of another role (Krackhardt 1999). Modern neuroscience supports the idea that cognition is inseparable from affect (Thagard 2006, Duncan & Barrett 2007), making the process of aligning social behavior subconscious. Affect is therefore linked to an individual's thoughts, identities and actions and, during interactions, people are driven by intuition to try to maintain affect (Heise 2007).

ACT enables the study of collaboration as it both accounts for dynamic behaviors of individuals and reveals the stable social order which emerges from these dynamics (Hoey, Schröder, & Alhothali 2016, Schröder et al. 2016). Social order is captured by the feedback loop created between individual actions and larger societal developments when people act in accordance with their identities (Heise 2007). As people internalize theories about social structure, anticipate behaviors of others, and incorporate culturally defined ideas into their self-concepts, identity ties individuals to social order (MacKinnon & Heise, 2010). The power of identity has been recognized by scholars in various fields, ranging from environmental behavior (Fielding, McDonald, & Louis 2008) and marketing (Berger 2014) to politics (Kinnvall 2004, Klandermans 2014) and economics (Akerlof & Kranton 2010, Akerlof & Kranton 2000). The affective process is gaining prominence in sociology and cognitive science (Heise 2007, Miles 2015, Schröder et al. 2016).

ACT, unlike most other symbolic interactionist approaches, relies on a mathematical formalization of affective meanings, impression formation processes, and interaction dynamics (Morgan et al. 2019). Affective meanings can be measured by Osgood's dimensions: evaluation (good vs. bad), potency (weak vs. strong) and activity (calm vs. excited), collectively known as EPA (Osgood et al. 1957). These universal semantic dimensions correspond to the basic dimensionality of social interaction and human emotion (Scholl 2013, Kajiç et al. 2019). According to ACT, these vectors represent social concepts denoting the types of persons, traits, actions, and social settings in three-dimensional EPA space (Osgood et al. 1975).

Cultural expectations are quantified in terms of EPA in patterns known as fundamental sentiments (Heise 2007). Fundamental sentiments express generalizations of how good/bad, strong/weak, and lively/calm particular identities, behaviors or emotions seem outside of the context of social events (Heise 2007). Within social events, there exist event-contextualized EPA meanings known as transient impressions. Transient impressions express the interpretations of actors and behaviors when they appear together in the context of events and are modeled using regression equations (Heise 2007). Transient impressions for specific social events are computed by inputting fundamental sentiments associated with particular denotative concept labels into ACT's impression change models, in which coefficients reflect culture-specific principles of social perception and action (Robinson et al. 2006). EPA vectors are collected in dictionaries which are obtained from empirical studies in which respondents rate hundreds of concepts (Osgood et al. 1975). Ratings can be interpreted as reflecting within-culture consensus of the affective meaning of human sociality; speakers of a common language have been found to generally agree upon the placement of social concepts in EPA space (Ambrasat et al. 2014, Heise 2010).

According to ACT, people act in alignment with their identities to maintain situational meanings and conform to normative cultural expectations (Heise 2007). When these expectations are violated and there is a discrepancy between the current experience and the expectation, people experience deflection. Cognitive consistency theories explore the idea that people act in a way that seeks to minimize deflection (Robinson et al. 1992). Therefore, the agent experiencing the most deflection is likely to be the next to act in the interaction and will choose an interaction partner who is most likely to confirm the sentiments associated with the actor's identity, the object-person's identity, and the behavior (Heise 2013). Deflection is calculated as the sum of the squared Euclidean distances between transient impressions τ_i of the identities and behaviors emerging from a situation (between a given "actor" and "object-person") and fundamental sentiments f_i for these event elements summed over EPA dimensions (with weights w_i): $D = \Sigma_i w_i (f_i - \tau_i)^2$ (Morgan et al. 2019).

2.4 Social Simulation Based on ACT

In the past, several ACT-based computational models have been developed and applied (Morgan et al. 2019). The mathematical formalization of ACT enables it to be used as a basis for defining computational agents using linear algebra (Heise 2007). Interact is the classic ACT simulation model, which generates behavior predictions using deflection minimization over summed EPA dimensions, weighted by coefficients that encode culture-specific principles of impression formation (Heise 1997). The predictions from this model have been supported by survey, experimental, and naturalistic evidence from a research program which developed over several decades (Robinson & Smith-Lovin 1992, Schroder & Scholl 2009, Heise & Lerner 2006). Group Simulator builds on Interact's social-dynamics equations to apply ACT to group interactions. Interact pertains to dyads; Group Simulator scales the model to triads and larger groups, adding additional assumptions that do not exist in Interact.

Group Simulator, like Interact, uses deflection-minimization as the optimization mechanism to simulate a relationship process of mutually compatible meaning-making (Morgan et al. 2019). The model predicts group members' behavioral and emotional responses to unfolding events based on the assumption that the agent experiencing the most deflection (social tension) will tend to be the next to act (Heise 2013). It then calculates the most likely interaction partner by optimizing for the agent that will best confirm the sentiments associated with the actor's self-identity, the object-person's self-identity, and the behavior (Heise 2013). Group Simulator functions according to the social psychological notion that action is a resource for reducing tension, and the individual in a group who most needs this resource seizes the moment, while others perceive that person's predicament and yield the floor. From a group standpoint, this corresponds to a strategy of controlling maximum tension within the group (Heise 2013). This extends the deflection-minimization imperative at the heart of the Interact models of dyadic interaction from shaping the particular behaviors and emotions that seem appropriate to the situation to additionally shaping who acts first and next in group interactions.

Group Simulator is a detailed computational model with empirically-based inputs to simulations. This results in a high amount of predictive precision compared to other theories of emotion which are limited to verbal descriptions (Kajic et al. 2019). Heise (2013) validated Group Simulator through the replication of empirical findings from a classic study of mock jury deliberations (Strodtbeck et al. 1957). The model predicts the affective misalignment experienced by each agent and the distribution of interpersonal behaviors in groups across Interaction Process Analysis (IPA) categories. The model integrates sentiment analysis methods and classifies EPA profiles for a predicted behavior into the IPA category with the most similar EPA profile (Heise 2013). This categorization is displayed in Figure 2.1.

IPA Category Number	IPA Category Name	Sample Behaviors	E	P	A
1	Shows solidarity	help, compliment, gratify	1.78	1.29	.21
2	Shows tension release	josh, laugh with, cheer	1.48	.91	1.12
3	Agrees	agree with, understand, accommodate	1.60	.78	.01
4	Gives suggestion	encourage, cue, coach	1.28	1.18	.25
5	Gives opinion	evaluate, analyze, entreat	.16	.59	−.02
6	Gives orientation	inform, educate, explain	1.68	1.62	−.14
7	Asks for orientation	quiz, question, ask about	.50	.62	.45
8	Asks for opinion	consult, prompt, query	.48	.74	.16
9	Asks for suggestion	entreat, ask, beseech	.30	.24	.09
10	Disagrees	disagree with, ignore, hinder	−1.00	.35	.45
11	Shows tension	fear, cajole, evade	−.89	−.16	.35
12	Shows antagonism	argue with, deride, defy	−.82	.71	1.32

Figure 2.1 Categories of IPA with sample behaviors and average evaluation, potency and activity scores for sample behaviors (Heise 2013)

2.5 Sentiment Analysis

Affect helps to control social interactions and sustain the social and cultural order (Heise 2007; Hochschild 1983; Kemper 2006; Von Scheve 2014). Just as affective alignment reveals how well someone is maintaining affect (Robinson et al. 2006), sentiment analysis, the interpretation and classification of emotions, can be used to analyze group interactions through ACT. Sentiment Analysis is gaining prominence in Machine Learning and Natural Language Processing yet has repeatedly faced challenges on software engineering data (Nakov et al. 2015). Sentiment Analysis research has focused on mapping content to either one-dimensional sentiments (positive vs. negative) or categorical label predictions (happy vs. sad) for large pieces of text. Previous work has inferred emotional meaning from subjective text using statistical Machine Learning and computational linguistics methods (Pang et al. 2002, Turney & Littman 2002). For example, some researchers have applied Sentiment Analysis toward word embedding and deep learning methods (Glorot et al. 2011, Socher et al. 2013). Affect research has generated limited insight into the dynamic mechanisms of emotion as it relies on experimental approaches and verbal theorizing (Reisenzein et al., 2013; Scherer, 2009). ACT introduces power and activity to complete the EPA space, enabling a more detailed, complex level of analysis of the sentiment of objective information (Alhothali and Hoey 2015). This approach will not only help advance theory behind he dynamics of affective alignment and sentiments, but also contribute insight into affective computing, the subfield of artificial intelligence which builds virtual agents (Gratch et al. 2015, Gratch & Marsella 2004, Hoey et al. 2016, Reisenzein et al. 2013).

2.6 Interaction Process Analysis & SYMLOG

Interaction Process Analysis (IPA) is a well-known taxonomy of group behavior (Bales 1999) that can be applied to group dynamics data produced by Group Simulator. IPA is a form of analysis which addresses both the theoretical and practical aspects of systems of human interaction. It provides a framework for classifying behavior, act by act, as it occurs in small groups (Bales 1999). There are twelve observation categories in IPA, which are grouped into four types of behavior: positive socio-emotive behavior, active task behavior, passive task behavior, and negative socio-emotive behavior.

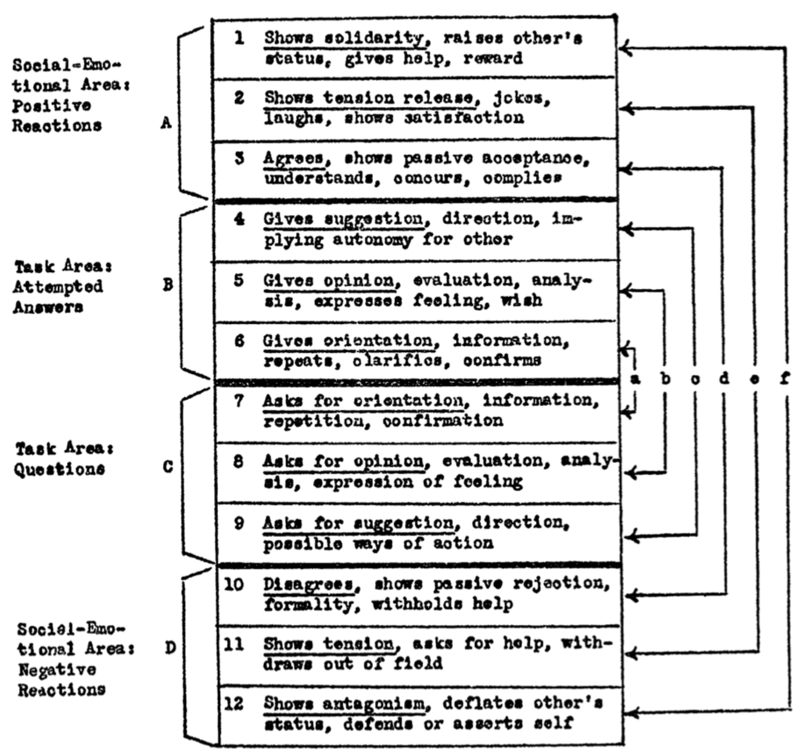


Figure 2.2 Observational Categories within IPA (Bales 1999)

In Figure 2.2, the labels to the left represent the four behavior types. Positive reactions are positive socio-emotive behavior. Attempted answers are active task behavior. Questioning is passive task behavior. Negative reactions are negative socio-emotive behavior. The IPA categories are also arranged into a series of complementary pairs which describe the implied theoretical content of the categories (Bales 1950). The connections to the right of Figure 2.2 represent these complementary pairs: a. problems of orientation, b. problems of evaluation, c. problems of control, d. problems of decision, e. problems of tension-management, and f. problems of integration. The key assumption of the IPA method is that the functional problems of interaction systems can be abstracted from all organized and cooperative systems of human interaction (Bales 1950).

Previous studies in THEMIS.COG have tied IPA categories to example pull request comments, as shown in Figure 2.3 (Heise et al. 2018). The IPA groups listed represent the four types of behavior, positive reactions are positive socio-emotive behavior, attempted answers are active task behavior, questions are passive task behavior, and negative reactions are negative socio-emotive behavior. Figure 2.3 shows how negative socio-emotive behavior is characterized by emotions such as aggression, nervousness, and defensiveness, which are disruptive, while active task behavior helps to advance or orient the group to the task.

IPA group	IPA category	Example pull request comment	Emotions
	Shows solidarity	*im sure you'll recover somehow*	Calm
Positive reactions	Shows tension release	*ooops sorry my mistake*	Sorry, careless
	Agrees	*allright will do thanks for the feedback*	Thanks, calm
	Gives suggestion	*needs a metric ton of docs*	Cautious
Attempted answers	Gives opinion	*love it*	Happy
	Gives orientation	*fucking hell I'm hungry now*	Aggressive, angry
	Asks for orientation	*what if the file does not exist*	Nervous, cautious
Questions	Asks for opinion	*what about filtering by type and tag*	Cautious
	Asks for suggestion	*how could i show the name of the fighter that wins the turn*	Calm, cautious
	Disagrees	*for me just says linux which is not very useful at all*	Aggressive
Negative reactions	Shows tension	*um i dont know i dont remember changing that and probably did it by accident*	Nervous, defensive
	Shows antagonism	*kill this method with an axe and then burn its body*	Defensive, aggressive

Figure 2.3 IPA Categories with GitHub Example Comments (Hoey et al. 2018)

IPA was extended to create a measurement system known as the System for Multiple Level Observation of Groups (SYMLOG) (Bales 1999). SYMLOG allows for the classification of behaviors into IPA categories, facilitating the use of past group data to validate results (Hoey et al. 2018). This theory uses a set of methods to measure the behavior of group members from the levels of perceptions, attitudes, values, concepts, non-verbal behavior, public behavior, and the content of the individuals' verbal communication (Polley et al. 1988). SYMLOG is used to better understand the individuals in a group (Wainer & Braga 2001) and is currently used as a consulting method. SYMLOG Consulting Group (SCG) was founded in 1983 by Robert Koenigs and Margaret Cowen with the support of Bales and has worked with corporations including Microsoft, Toyota, IBM, Citibank and Mercedes Benz ("What is SYMLOG?" n.d.). The exceptional results of SCG and the SYMLOG method highlight the relevance and importance of better understanding effective leadership and group dynamics, not only in the academic sphere, but also the public sphere. Group Simulator capitalizes on the powerful frameworks of ACT and IPA to model how affective dynamics guide the evolution of social ties and networks over time, shaping identity processes and motivating interpersonal behavior. I use the EPA categories from ACT to input cultural sentiments into the model and analyze the predicted IPA behavior categories to better understand behavior dynamics for each simulated group interaction.

2.7 Group Dynamics

Group Simulator predicts interpersonal behaviors in groups across IPA categories, guided by theories from Bales, the twelve categories and definitions listed in the Figure 2.2. IPA categories can be used to better understand behavior dynamics within groups and measure the balance of certain behaviors (Bales 1970). Figure 2.3 is a compilation of the raw scores obtained from all interactions observed by Bales through 1999, including percentage rates and suggested limits. The suggested limits were established for each category using the binomial confidence limits found in *Statistical Methods* (Snedecor 1946) and the values listed represent percentage values, totaling 100 percent (Bales 1970). The suggested limits provide guidelines for effective tasks groups and suggest that larger values of active task and positive socio-emotive behavior produce more effective teams (Bales 1970).

Category	Raw Scores	Per-centage	Suggested Limits for Inspection of Profiles*	
			Lower	Upper
1	246	1.0	0.0	5.0
2	1675	7.3	3.0	14.0
3	2798	12.2	6.0	20.0
4	1187	5.2	2.0	11.0
5	6897	30.0	21.0	40.0
6	4881	21.2	14.0	30.0
7	1229	5.4	2.0	11.0
8	809	3.5	1.0	9.0
9	172	.8	0.0	5.0
10	1509	6.6	3.0	13.0
11	1009	4.4	1.0	10.0
12	558	2.4	0.0	7.0
	22970	100.0		

Figure 2.4 Raw Scores and Suggested Limits (Bales 1999)

Bales suggests the limits shown in Figure 2.4 and makes several generalizable conclusions about effective groups. Bales argues that disagreements inevitably develop, creating tensions that must be resolved through socio-emotive behavior to maintain group solidarity (Bales 1970). Groups must have more positive socio-emotive behaviors than negative socio-emotive behaviors for effective task accomplishment (Bales 1950). Positive socio-emotive behaviors are about twice as common as negative ones (Bales 1999).

Socio-emotive and task role differentiation is hypothesized to result from an inequality of participation in task-oriented activity (Burke 1967). Task acts, acts designed to reach a goal, result in tension and hostility (socio-emotive problems) as when one person engages in task behavior, another is denied the opportunity (Burke 1967). Meaningful coordination requires an inequality of participation in task actions as not everyone can act at the same time, but the person who is highly active is the primary source of tension (Burke 1967). This role differentiation is less likely to develop in groups when a leader is indicated and accepted as the leader by other members of the group (Verba 1961). A legitimate leader does not need to openly validate their position; they have time to engage in expressive-supportive activity, reducing the number of socio-emotive problems (Burke 1967, Olmstead 1954). Bales and other status theorists have found that leadership corresponds with perceived task competence (Bales 1950, Bales 1970, Berger et al. 1974). Perceived competence correlates significantly with active task behaviors and negative socio-emotive behaviors (Ridgeway & Johnson 1990). This indicates that negative socio-emotive behavior is more common from leaders of the group (Slater 1955).

These theories are grounded in the definitions of socio-emotive behavior as positive behaviors such as agreeing, seeming friendly, and dramatizing and negative behaviors such as disagreeing, seeming unfriendly and showing tension. Task behaviors are defined as those which contribute to the shared task (Bales 1970). Task behaviors are defined as active task if the behavior involves contributing to the shared task by giving suggestions, evaluation or information. Passive task behavior is characterized by questioning or asking for information, an opinion, suggestions or direction (Bales 1970). Ridgeway and Johnson suggest that if another member's task suggestion is judged useful or useless by a second member, task concerns alone are likely to induce the second member to express agreement or disagreement with the first member. Their analysis shows that while members are task-oriented, agreements and disagreements with task suggestions are first and most directly task rather than socio-emotive behaviors (Ridgeway & Johnson 1990). Ridgeway and Johnson present an analysis which indicates that these categories of behavior interact to shape the behavior dynamics of the group.

Bales completed a large research program and included many replications to gather the findings shown in Figure 2.3, but this process was expensive, labor intensive, time consuming, and depended on the capability and training of expert coders (Hoey et al. 2018). Given the labor intensive, qualitative coding this work required, studying large numbers of groups to reach generalizable conclusions results in a scaling problem (Hoey et al. 2018). Group Simulator automates this process using agent-based modeling and even improves upon the computational methods for the study of group dynamics which often incorporate assumptions that are not theoretically or empirically grounded (Hoey et al. 2018).

2.8 Successful Task Groups

The broader literature suggests that successful teams have a meritocratic, rational culture (Weber 2004, Wiggins & Crowston 2010), a charismatic, capable and experienced leader (Weber 2004, Luther et al. 2010), a modular, granular division of labor (Benkler 2006, Weber 2004), frequent communication within the group (Luther et al. 2010), foster intrinsic motivation and self-selection for tasks (Benkler 2006, Weber 2004), and the use of collaborative technologies, such as to-do lists and mailing lists (Yamauchi et al. 2000, Gutwin et al. 2004). Some of these themes can be processed through the use of EPA vectors from INTERACT and GitHub dictionaries creating ratings which reflect cultural consensus of social concepts such as for identities like an experienced leader (Osgood 1975, Heise 2013). Scholars have looked at the ideal types of leadership as patterns of affective meaning. Using simplified empirical measures, negative (-), neutral (0), and positive (+), they found that authoritarian leaders are operationalized with the EPA profile E+ P+ A0, charismatic leaders are E+ P+ A+, and coercive leaders are E- P+ A+ (Schneider & Schröder 2012). As mentioned above, a charismatic leader is a suggested part of a successful team (Weber 2004, Luther et al. 2010). By exploring differences in evaluation (good vs. bad), my work offers a way to observe changes in affective alignment and behavior dynamics in groups that may be characterized as having a more charismatic leader (E+) compared to a more coercive leader (E-), through the lens of how the entire group dynamic is impacted by these changes.

I study group leadership through the lens of group dynamics and affective misalignment. By identifying threshold values between authority, charisma, and coercion as agents' characteristics in relation to other members of the group, my work analyzes the impact of changing the evaluation and potency values of leaders and group members. Managers in the United States in 1978 followed the typical EPA pattern of authoritarian leaders. Because they were acknowledged leaders, they did not need to communicate their power through expressive actions (Schneider & Schröder 2012). My work will also contribute to growing literature studying power dynamics by exploring differences in potency (powerful vs. weak), both between members of the group and identifying boundary conditions by using potency gradients which are centered around 0 or around +1.0 to explore the importance of a zero threshold.

2.9 Online Collaborations

Understanding the social forces behind self-organized collaboration is becoming increasingly important as the creation of economic value and political problem-solving transitions to an informal, online setting. Previous research into online collaboration has focused on understanding how the political nature of open source software development can make participants more successful in development (Ducheneaut 2005), how social interactions (Tsay et al. 2014) and geographical locations (Rastogi et al. 2016) can indicate which developers' contributions get accepted in an open source project on GitHub, and how IPA values predict the acceptance of a pull request (Rishi 2017). These findings have focused on the experiences of individual team members within groups. Previous research on online group dynamics has explored group structures, but there is limited research considering both the meanings of the identities that define a culture and the impact of relational norms.

Research on group dynamics is divided about the benefits and drawbacks of particular group structures. While some scholars find that hierarchical structures, interactions in which a group member is in a position of structural power, lead to more successful online collaborations and believe that egalitarian codependent collaboration, interactions in which all group members interact equally, cannot be a reality with versatile, reliable and profitable applications (Healy & Schussman 2003, Daniel et al. 2018), others find a repeatedly consensus-driven, egalitarian nature of open source groups (Moody 2001). Recent research on how role configurations and relational norms influence group behavior has found that hierarchical groups tend to experience less deflection, or violation of group members' expectations, with members in dominant roles experiencing more violation (Morgan et al. 2019). Relational norms also allow group members to resolve deflection through reciprocation, an important implication for egalitarian groups without clear expectations to establish dominance patterns (Morgan et al. 2019). Others have found that while relational norms such as reciprocity create a smaller power gradient between team members, the ability to address the group for prolonged periods underscores the social distance between group members (Gibson 2010). Previous literature offers some insights about group structure or cultural / identity dynamics, but not about the impact or intersections of these two factors.

Though researchers have examined the operation and maintenance of hierarchy formation in groups for decades (Skvoretz 1988), there are few generative models of these dynamics (Ridgeway and Balkwell 1997). Group Simulator is the only model that applies an identity maintenance perspective (Morgan et al. 2019). The THEMIS.COG extension of Group Simulator is the first model that allows simultaneous modeling of network structures and identity maintenance / cultural factors in the same simulation model. I expand on previous research by exploring the intersections of cultural sentiments and network structures and use sentiment analysis to explore the relationship between affective alignment and behavior dynamics in groups. My work contributes to growing the literature studying dynamics in online groups by exploring the impact of affective values on group dynamics.

Chapter 3 - Research Design

3.1 Overview

To examine how both hierarchies of network structure and of the cultural sentiments associated with agent identities shape patterns of affective alignment and behavior dynamics in collaborative task groups, I use GroupSimulator to simulate interactions in groups (1) that have hierarchical vs. egalitarian group structures and (2) for which agent identities carry different EPA values of evaluation and potency. I study groups which are collectively oriented and task-oriented. Group structure is defined as egalitarian if all agents can act on each other and are acted upon by all other members of the group, and hierarchical if certain agents cannot act on other agents or are not acted on by others. Cultural sentiments are varied using EPA vectors which model human sociality (Heise 2010) in order to observe status and power disparities.

I employed a 2x2x8x10 design, comparing simulation predictions about group-level deflection, affect control theory's measure of affective alignment, and behavior dynamics for two group structures (egalitarian and hierarchical) over two identity dimensions (evaluation and potency) altered for eight levels of agent identity distance over deciles of address to group rates. I conducted 100 simulations for each identity dimension with respect to each group type and each percentile. Each simulation consisted of 500 exchanges of behavior among the simulated agents. The resulting 16 million simulation iterations are a representation of 16 million hypothetical group interactions. These data provide predictions and hypotheses for future research to validate. When the relative potency of the agents was varied, I held the evaluation and activity of the agents constant at a value of 1.0 to isolate the effects that relational norms have on power dynamics. When the relative evaluation of the agents was varied, I held the potency and activity of the agents constant at a value of 1.0 to isolate the effects that relational norms have on evaluative dynamics.

The address to group rate sets the probability that the actor and recipient of the last action simply reverse. It ensures that actors will direct some of their actions to the group as a whole rather than to specific individuals. A value of 0.0 stops forcing the whole group as a recipient of an action and 1.0 eliminates dyadic interaction in the group. A value of 0.4, which assures that about forty percent of actions are directed to the whole group rather than to individuals, is typical in task-oriented groups (Strodtbeck 1954). In this research, the address-to-group rate was varied by deciles, and when its effects were not being observed, was held constant at 0.4. The EPA values and address-to-group rate selected for each experimental condition are defined in tables in Chapter 4.

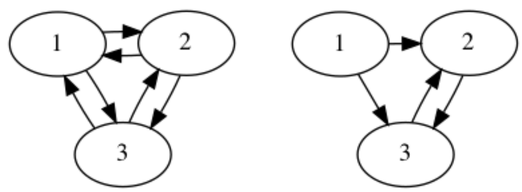
3.2 Group Size

Group size can be varied in Group Simulator from 3 to 25 agents. Group Simulator imposes a one-at-a-time principle on simulated interactions, in which interactions take place in a single-line, like in classroom discussions. For all simulations reported in this study, group size was held constant at three. While teams are often larger than triads, interactions involve three types of agents: actors, recipients, and observers. Focusing on triads enables me to analyze the most realistic group interaction given the single line of interaction constraint. Theory from Simmel suggests that the differences in interactions between a triad and a larger group are minimal, supporting that my findings can be taken as implications for situations in triads as well as larger groups (Krackhardt 1999).

3.3 Group Structure

Group Simulator allows group structure to be input through a network matrix and functions with the assumption of group boundaries. In these matrices, 1 represents a tie between two agents while a 0 represents the lack of a connection. For example, the matrix (0, 1, 1), (1, 0, 1), (1, 1, 0) would indicate that agents 1 and 2 can interact, agents 1 and 3 can interact, and agents 2 and 3 can interact, but none of the agents can interact with themselves. In this example, each agent can interact with the other agents and each is acted upon equally, but agents cannot interact with themselves.

There are two network structures in this study. The structures selected include Network E, an egalitarian structure in which all agents act and are acted upon equally, and Network H, a hierarchical structure in which Agent 1 acts upon Agent 2 and Agent 3, Agent 2 and Agent 3 act on each other, and no one can act on Agent 1. Network E is mapped by the matrix (0,1,1), (1,0,1), (1,1,0) and Network H is mapped by the matrix (0,1,1), (0,0,1), (0,1,0).



Network E Network H

These network structures were chosen to represent two different group structures of the five group structures which exist on GitHub. The five structures range from a structure with a very clear and strict hierarchy to an egalitarian structure (Zoeller et al. 2019). I focus on the two extremes, the egalitarian structure and the strict hierarchical structure to avoid the complexities of the intermediary structures. Network E represents a typical egalitarian network in which all agents can act and are acted upon equally. Selecting Network E was an intuitive choice to study group structure as Network E is a common representation of egalitarian group structure. The focus of Network H is the constructed hierarchy between Agent 1 and Agents 2 and 3. The structural power of Agent 1 in this network is created by the impression dynamic of object diminishment effect, which is the loss of power an identity experiences from being the object of an action. As Agents 2 and 3 experience this effect as Agent 1 acts on them, but Agent 1 experiences no object diminishment as no one can act on Agent 1, Agent 1 is in a position of structural power.

When assigning agent identities in simulations, Agent 1 will be assigned a unique identity in hierarchical conditions. Agents 2 and 3 will be given identical identities to examine how group structure interacts with the cultural sentiments associated with identities, and how and when each contributes to groups' affective alignment and behavioral dynamics.

3.4 Agent Identities

I incorporate cultural sentiments into the simulations when specifying the identity for each agent. Using Affect Control Theory (ACT), each actor is defined by EPA, evaluation (good vs. bad), potency (powerful vs. powerless), and activity (lively vs. inactive), values to create a mathematically understandable identity (Heise 2007). EPA values are measured on a scale from -4.3 (infinitely bad, powerless, or inactive) to +4.3 (infinitely good, powerful, or lively) (Osgood et al. 1957). To select and understand EPA values in the context of collaborative groups, I reference two cultural dictionaries. As dictionaries are compiled through empirical studies in which respondents rate concepts, the ratings reflect the placement of characteristics and identity roles in EPA (Heise 2010). Interact (Heise 2001) is a web-based computer program that mathematically and empirically operationalizes ACT principles. I use the dictionary Indiana 2002-2002 in Interact (Francis and Heise 2006). I interpret the verbs as behavior expectations that match cultural stereotypes and are generated by affective processes. The second dictionary I refer to is the GitHub dictionary. This dictionary was compiled by collecting cultural data specific to users. As the collected ratings vary due to the activity level of the user on GitHub, I will use the modal EPA value for the mode containing the largest proportion of raters when I discuss GitHub rating.

As my research questions focus on the impact of hierarchies of network structure and cultural sentiments on affective alignment and behavior dynamics, the links between evaluation and status and potency and power are important in helping me explore this question. In this study, I vary evaluation and potency to analyze these theoretical relationships while holding the third dimension in ACT, activity, constant. To explore the impact of evaluation and potency on behaviors and deflection experienced, I separately manipulated the identity distance between Agent 1 and Agents 2 and 3 on evaluation and potency to isolate the impact of each of these affective dimensions on measured outcomes. In the conditions isolating potency, I hold evaluation and activity values at 1.0 and increased the difference in potency values between Agent 1 and Agents 2 and 3. In the conditions isolating evaluation, I hold potency and activity values constant at 1.0 and increase the difference in evaluation values between agent 1 and agents 2 and 3 at varying increments. I analyze these differences in increments on the 8.6 point scale from -4.3 to +4.3. The agent distance is increased in increments ranging from 0.1 to 1.0 for both evaluation and potency. Though my full analysis includes evaluation and potency distances on the full 8 point scale, my analysis relies mainly on differences in identity values of 0-2 as these are the most common identity distances found in task groups and on GitHub.

3.5 Impression Dynamics

As explained in the literature review, Group Simulator, like ACT, simulates impression dynamics using culture-specific impression formation equations that predict transient impressions of events and resultant behavior dynamics from fundamental sentiments about interactants' identities. In this research, I am using the unisex impression formation equations for U.S. English language culture (Robinson & Smith- Lovin 1992), which are based on data collected from American college students in 1978. The equation I implement aggregates male and female coefficients using a structural equation model (Heise 2013), reflecting general principles guiding event processing among U.S. English speakers. This equation best fits with the cultural dictionaries used in my research, which summarize fundamental sentiments for identities and behaviors among U.S. English speakers.

3.6 Selection of Actors

Group Simulator applies ACT to determine what behavior a given actor will enact toward a given recipient (Heise 2013). This selected behavior transforms current impressions about the actor and recipient into new impressions that are closer to the fundamental sentiments of the actor and recipient (Heise 2013). This process is particularly complex in small groups where any multiple of individuals can initiate the next action and any other individual, or even the whole group, might be the recipient of the actor's behavior (Heise 2013). Group Simulator therefore includes inputs, which control the selection of actors and recipients of action. For actor-choice, this study uses the maximum self-tension criterion. This means that group members yield to the individual who is experiencing the most personal tension, i.e. the individual whose transient impression most deviates from their fundamental sentiment (Heise 2013). The maximum self-tension criterion corresponds to the notion that action is a resource for reducing tension (Heise 2013). Maximum self-tension provides a basis for actor selection that successfully reproduces four empirically observed phenomena: 1. distributions of actions in IPA categories; 2. male-female differences in IPA distributions; 3. rank-frequency distributions of acts initiated by different group members, and 4. male-female differences in numbers of acts initiated (Heise 2013).

3.7 Other Settings

Group Simulator allows for several other parameters which are held constant as control values in my research and set for each condition of the simulations.

3.7.1 Reciprocity

After each event, Group Simulator determines whether a reciprocal interaction sequence is in progress. Conversation analysts commonly find reciprocation in discourse, with actor and object roles passing back and forth between two individuals and other group members being excluded from participation for a period of time. A back-and-forth exchange can extend through numerous events, especially when two individuals are in conflict over some issue. The reciprocity rate indicates the proportion of actions reciprocated by the actor. A value of 0.8 assures that about eighty percent of actions are reciprocated (Heise 2013). In these simulations, the reciprocity rate is held constant at 0.8, simulating commonly observed rates of reciprocity in task groups (Strodtbeck 1954).

3.7.2 Individuality and Initial Tension

Individuality settings in Group Simulator specify the extent of variations in self-sentiments resulting from combining statuses and traits with an identity, thereby adding another measure of sociality to the model. 1.0 is the approximate standard deviation when amalgamating all traits in the Interact dictionary with an identity, so I set individuality at a default value of 1.0 for these simulations. This is consistent with previous work (Heise 2013). Initial-tension sets the standard deviations on EPA dimensions similarly to individuality, but impacts group processes only for a short while until the impressions of agents themselves and others change from participating in social interaction. Initial-tension is set to 1.0 in this study as this setting has been shown by prior work to generate impression states corresponding to typical emotions (Heise 2013).

3.8 Statistical Significance Testing

In order to test the statistical significance of my results, I ran Van der Waerden tests with the Bonferroni correction. Though I had originally intended on running an ANOVA test, the deflection distributions of my data are skewed as they are long-tailed distributions, shown in Appendix A. The residuals around the mean are unlikely to be normally distributed, which is a violation of ANOVA. I performed the Kruskal Wallis test to see if there were group-level differences in variation and found significant support for the alternative hypothesis: the groups' variation is heterogenous. Consequently, I performed the Van der Waerden test, which is a non-parametric alternative to ANOVA, with a Bonferroni Correction. I used the Bonferroni correction as my data is at a risk for swamping, with a very large sample size from running over 16 million simulation iterations. The Bonferroni correction is a multiple-comparison correction that is used when several statistical tests are being performed simultaneously. Given the size and number of variables in my data set, the Van der Waerden test will be performed simultaneously on data with many differing variables, so the Bonferroni correction is used in order to avoid a lot of spurious positives. The correction lowers the alpha value to account for the number of comparisons being performed.

I ran four Van der Waerden tests, for each of the two network structures within evaluation and each of the two network structures within potency. All tests indicated p-values of 2.0×10^{-16}. The p-values are all significant at the 0.01 level, showing massive significance, with no variation in significance. The distributions of my data and the Van der Waerden test results are included in Appendix A.

Chapter 4 - Results

In this chapter, I show how my results predict that hierarchies of network structure and cultural sentiments impact affective alignment and behavior dynamics in collaborative task groups. The two research questions which I explore through my results are 1) how hierarchies shaping what we can and should do within groups impact the tension from affective misalignment and 2) how hierarchies shaping what we can and should do within groups impact behavior patterns. I examine the impact of these functional limitations through several simulation conditions. To isolate the effects of evaluation and potency distance, I hold the address to group rate constant at 40% for the figures in this chapter.

I begin with the first research question, showing results for how the two dimensions of hierarchy impact the deflection (tension that arises when a group members' expectations are violated) experienced. First, I observe how network structure and differences in status and power constrain and enable role performance. Second, I observe differences in the magnitude of impact evaluation distance as compared to potency distance on the median deflection experienced. In other words, I compare the impact on group dynamics of differences in status and differences in power between members.

Next, I address the second research question, showing results for how the two dimensions of hierarchy impact behavior dynamics. I analyze the task behavior and socio-emotive behavior produced as the evaluation distances and potency distances increase over gradients with distances ranging from 0 to 8. In order to explore the distinctions of being fundamentally good or bad and fundamentally strong or weak, I then observe predicted behavior dynamics in groups with positive evaluation and potency identity values with distances ranging from 0 to 2 compared to groups with both negative and positive evaluation and potency values with distances ranging from 0 to 2. These comparisons allow me to explore the importance of the zero threshold, the difference between group interactions of members who are all fundamentally good or strong with groups of mixed identities. These results explore the evaluation homophily which exists in society, such as how people don't want to spend time with terrible people and push them out, through the lens of behaviors produced in these groups. These results will be further contextualized and discussed in Chapter 5.

In addition to these results, I observed several other trends which I have included in Appendix B for reference if there is interest. In Appendix B, I share my results which predict the impact of varying the proportion of actions addressed to the group and which examine how the positive and negative evaluation and potency distances impact affective alignment experienced by different members of the group.

4.1 How Network Structure and Culture Constrain and Enable Role Performance

Figure 4.1 examines agents' median deflection as a function of evaluation distances between agents' identities. I initialize simulations in Figure 4.1 with the identity values displayed in Table 4.1.

E Distance	Agent 1: E	Dictionary Identity	Agents 2&3: E	Dictionary Identity	P	A	Address to Group
0	0	critic	0	critic	1	1	0.4
1	0.5		-0.5		1	1	0.4
2	1.0	project member	-1.0	opponent	1	1	0.4
3	1.5		-1.5		1	1	0.4
4	2.0	organizer	-2.0	enemy	1	1	0.4
5	2.5		-2.5		1	1	0.4
6	3.0	contributor	-3.0	bully	1	1	0.4
7	3.5		-3.5		1	1	0.4
8	4.0	angel	-4.0	devil	1	1	0.4

Table 4.1 Identity values selected to represent the gradient of evaluation distance in increments of 1.0 (+0.5 to Agent 1 and -0.5 to Agents 2 and 3 for each step) while holding the address to group rate constant at 0.4.

Agent 1 represents the higher status or more powerful member of the group and Agents 2 and 3 represent the lower status or weaker members. The predicted experiences of Agent 1 are plotted as solid lines. As Agents 2 and 3 have equivalent identity sentiments and are predicted to experience very similar patterns of deflection, the following figures combine these agents and plot their shared experience as dashed lines.

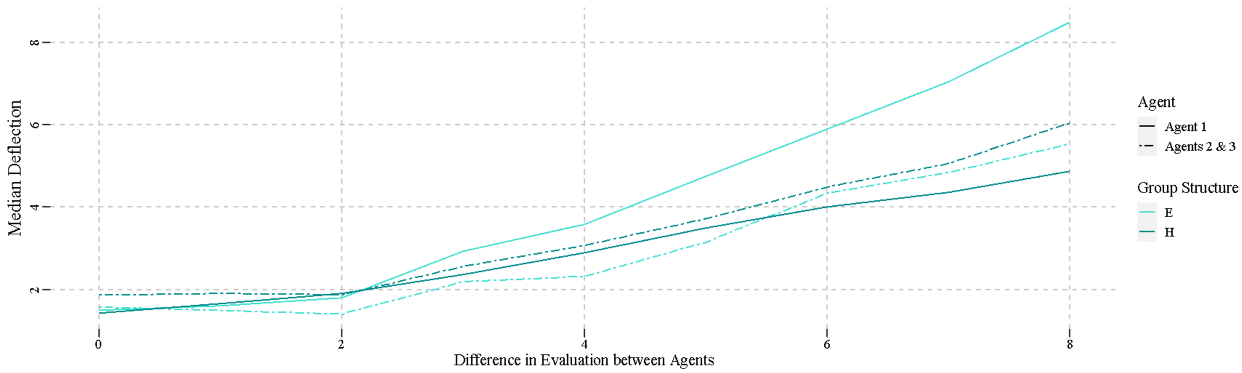


Figure 4.1 Median Deflection for Agent 1 (solid lines) and Agents 2 & 3 (dashed lines) at each level of evaluation distance between agents for egalitarian (light cyan) and hierarchical (dark cyan) network structures.

Figure 4.1 shows how network structure and differences in status constrain and enable role performance. As the evaluation distance between these agents increases, the deflection experienced by Agent 1 and Agents 2 and 3 increases at different rates. Agents 2 and 3 experience similar increases in deflection in both the egalitarian and hierarchical network structures as the evaluation distance increases. By an evaluation distance of 2, the deflection experienced by Agent 1 increases at a greater slope in the egalitarian network structure than for the hierarchical network structure. In the hierarchical structure, Agents 2 and 3 experience slightly more deflection than Agent 1, while in the egalitarian structure, Agent 1 experiences much more deflection. When the evaluation distance between Agent 1 and Agents 2 and 3 increases above 2, the agent with increasing status experiences much more affective misalignment than the agents with decreasing statuses. I do not include confidence intervals in Figure 4.1 as the intervals are so narrow, they are not visible in the figure. The data shown in Figure 4.1, and all of my simulation data, was statistically significant at a 0.001 level. Appendix A includes details of the statistical significance tests I completed.

My findings suggest that with an evaluation distance of 2 or greater, the group member who is perceived as better will experience significantly more unease. The y-axis scale of deflection values ranging from less than 2 to 8 shows a normal range of deflection experienced in groups. This group could be characterized as an interaction between two outlaws with EPA (-1.68, 0.68, 1.44) and a public defender with EPA (0.88, 0.81, 1.01). The public defender is predicted to experience more tension because of their expectations being violated than the outlaws, especially if all members of the group are structurally equal, so each member acts and is acted upon equally by other members. This finding predicts that in a group in which one member is assumed to be fundamentally good, while other members are assumed to be fundamentally bad, group dynamics are greatly disrupted. Figure 4.1 suggests that the distinction of being fundamentally good or bad an important factor in group dynamics and causes problems in collaborative task groups.

The next figure explores how network structure and power differences constrains and enable role performance. This is observed through the variation in deflection experienced by Agent 1 and Agents 2 and 3 as the potency distance between these agents increases. Table 4.2 displays the identity values used in Figure 4.2.

P Distance	E	Agent 1: P	Dictionary Identity	Agents 2&3: P	Dictionary Identity	A	Address to Group
0	1	0	assistant	0	assistant	1	0.4
1	1	0.5		-0.5		1	0.4
2	1	1.0	project member	-1.0	intern	1	0.4
3	1	1.5		-1.5		1	0.4
4	1	2.0	superior	-2.0	toddler	1	0.4
5	1	2.5		-2.5		1	0.4
6	1	3.0	project owner	-3.0	baby	1	0.4
7	1	3.5		-3.5		1	0.4
8	1	4.0	infinitely powerful	-4.0	infinitely powerless	1	0.4

Table 4.2 Identity values selected to represent the gradient of potency distance in increments of 1.0 (+0.5 to Agent 1 and -0.5 to Agents 2 and 3 for each step) while holding the address to group rate constant at 0.4. Figure 4.2 displays simulations run

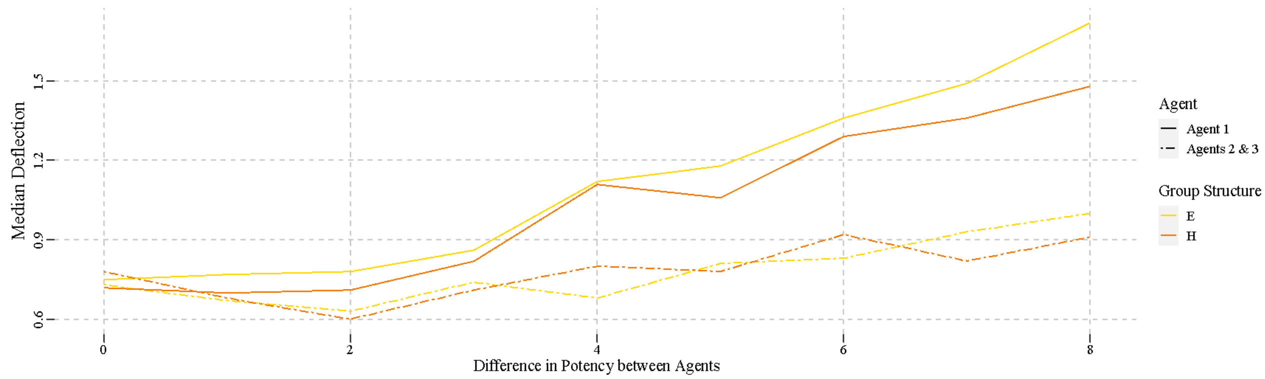


Figure 4.2 Median Deflection for Agent 1 (solid lines) and Agents 2 & 3 (dashed lines) at each level of potency distance between agents for egalitarian (light orange) and hierarchical (dark orange) network structures.

Figure 4.2 predicts that Agent 1 experiences a greater increase in deflection than Agents 2 and 3 as the potency distance increases in both the egalitarian and hierarchical network structures. Network structure impacts the predicted deflection experienced over the increasing potency distance as Agent 1 experiences more deflection in the egalitarian structure compared to the hierarchical structure. For small distances in potency, Agent 1 experiences fairly constant deflection until about a distance of 2, when the slope begins to increase. Agents 2 and 3 experience a different pattern. The deflection experienced by these agents decreases between the distances of 0 and 2, and then increases but fluctuates as the distances increase beyond 2. As ACT predicts that agents that are acted upon by agents with equivalent potency will experience more deflection than agents acted upon by more potent identities (Morgan et al. 2016), the decrease in deflection between distances of 0 and 2 is expected. Similarly, the greater affective misalignment experienced in egalitarian group structures can be rationalized as members in hierarchical groups experience lower levels of uncertainty given their explicit roles in the group, which increasingly align with their cultural sentiments as the distance in potency increases.

My findings suggest that with a potency distance of 2 or greater, the group member perceived as more powerful or authoritative will experience more affective misalignment. In a group with two interns (1.31, -0.82, 0.56) and an employer (1.26, 1.94, 1.09), the employer is predicted to experience more unease or tension due to their expectations being violated, especially if the interaction has an egalitarian network structure. Given the smaller scale of median deflection in Figure 4.2, it is important to note that this figure suggests interesting findings in the difference in deflection experienced as a result of the role of the group members. The amount of deflection experienced is quite low, predicting that power disparities in groups do not significantly increase the tension or unease of group members. However, the member in a position of authority will experience more tension relative to the other members as the power disparity increases.

4.2 The Magnitude of Impact on Deflection of Status Differences Compared to Power Differences

Figures 4.1-4.2 reveal increasing median deflection as evaluation and potency distances between agents increase. Figure 4.3 combines Figure 4.1 and Figure 4.2 to illustrate that the impact of increasing evaluation distance between agents is larger than that of increasing potency distance.

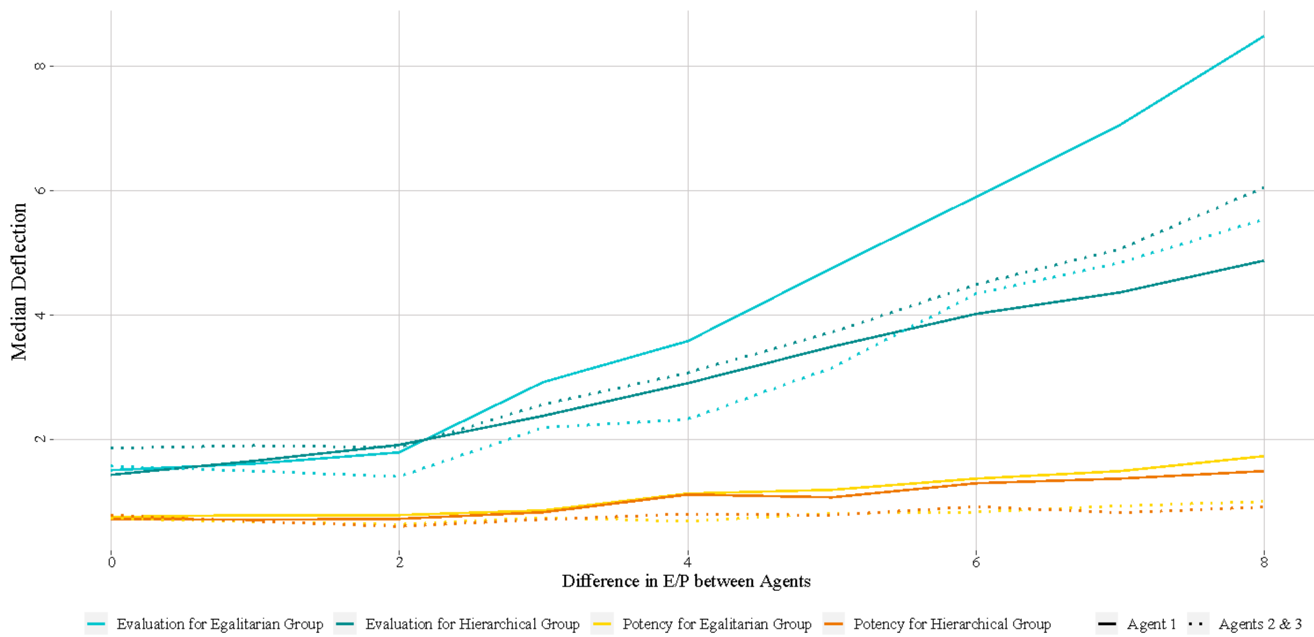


Figure 4.3 Median Deflection over Potency and Evaluation Gradients with agent differences varying from 0 to 8 in two group structures, egalitarian and hierarchical, for two agent roles

Figure 4.3 uses the evaluation and potency gradients defined in Tables 4.1 and 4.2. Figure 4.3 shows how a one-unit increase in agents' evaluation distance produces a greater increase in median deflection than a one-unit increase in agents' potency distance. This increase is apparent in Figure 4.3 beginning at distances of 2, and increases drastically as the evaluation distance and potency distance identity values of the agents increase. Differences based on agents' evaluation distance are greater in the egalitarian network structure than the hierarchical structure. In the egalitarian network structures, deflection experienced by the member of the group with greater potency or evaluation is much greater than for the agents with lower evaluation or potency identity values. The differences between network structures based on agents' potency distance are dwarfed by comparison to the magnitude of difference based on evaluation distance.

Figure 4.3 shows how much differences in status, such as respect or esteem, between members of the group increases the amount of tension experienced by the members. Though differences in power, such as authority or control, also increase the violation of a members' expectations, differences in status increase the affective misalignment to values four times as great as those of differences in power. The impact of status distances are of a much greater magnitude than those of power distances.

Referring back to the examples I used for the identity roles in Figure 4.1 and Figure 4.2, these findings suggest that the amount of tension due to their expectations being violated that the public defender is predicted to experience is much greater than the amount the employer is predicted to experience in their interactions with outlaws and interns, respectively. My findings show that status differences in a group impact tension and unease much more than power differences. These findings suggest the importance of perception of status, such as respect and esteem, between group members and have interesting implications for collaborative task groups.

4.3 How Network Structure and Culture Shape Behavior Dynamics

The previous figures have observed the impact of the two dimensions of hierarchy on the affective misalignment experienced in groups. In order to explore the influence of these hierarchies on behavior dynamics in these groups, the following figures use Interaction Process Analysis (IPA) to observe changes in behaviors present in these groups. As explained in my literature review, IPA uses twelve categories to analyze group behavior (Bales 1999). These categories reflect four different types of behavior: active task behavior (gives suggestion, gives opinion, gives orientation), passive task behavior (asks for orientation, asks for opinion, asks for suggestion), positive socio-emotive behavior (shows solidarity, shows tension release, agrees), and negative socio-emotive behavior (disagrees, shows tension, shows antagonism) (Bales 1999). Figure 4.4 shows how the patterns of group behavior predicted by the simulations are distributed across IPA categories as the evaluation distance between agents increases, using the definitions of evaluation distances specified in Table 4.1.

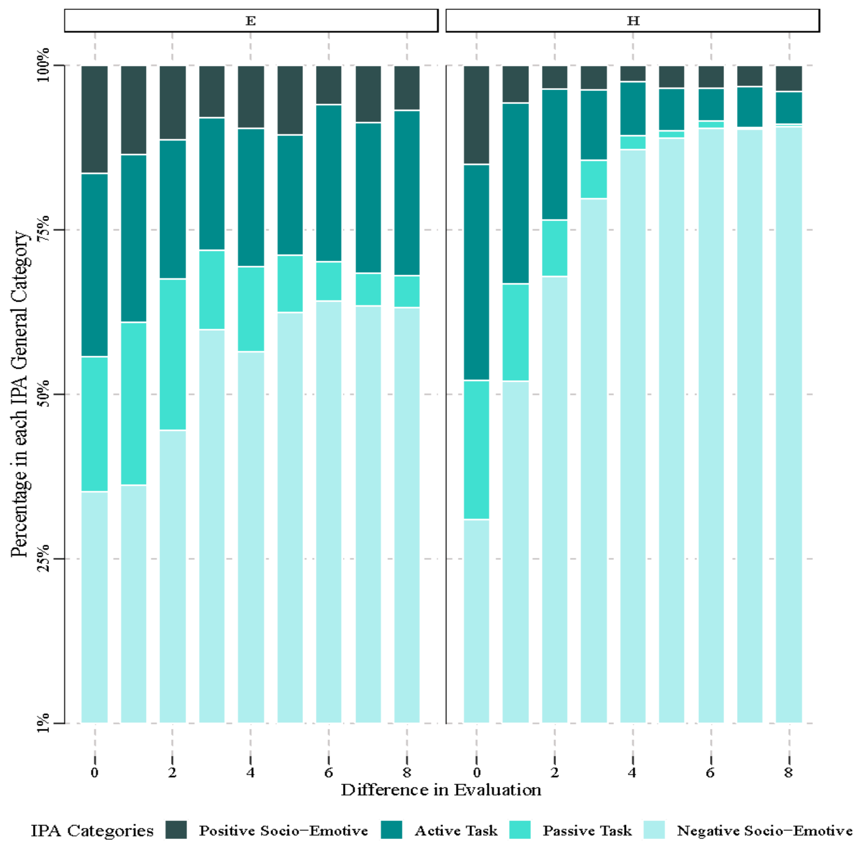


Figure 4.4 IPA Categories for Evaluation Gradient from E = -4 to E = 4. Network structures are represented by the two columns, E for egalitarian and H for hierarchical.

Figure 4.4 shows a large amount of negative socio-emotive behavior produced in groups with evaluation distances. In both network structures, these behaviors increase as the evaluation distance between agents' grows. In the egalitarian group structure, positive socio-emotive behavior and active task behavior decrease only slightly as the gradient increases, while passive task behavior decreases more significantly as negative socio-emotive behavior increases. By an evaluation distance of 5, the behavior patterns produced are fairly constant. In the hierarchical group, however, active and passive task behavior and positive socio-emotive behavior decrease as negative socio-emotive behavior continues to increase with additional evaluation distance. By an evaluation distance of 5, 90% of the behavior produced in the group is negative socio-emotive behavior.

Figure 4.4 shows that as the difference in status between members increases, predicted behaviors are overwhelmingly categorized as negative socio-emotive behavior, meaning the group experiences increasing disagreement, tension and antagonism. In the network structure E where all members interact equally, active task behavior remains constant, so members continue to give suggestions, opinions and orientations, and passive task and positive socio-emotive behavior fluctuate and decrease slightly. This means that some agreement, showing of solidarity, tension release and asking for orientation, opinion and suggestion remain present. In the network structure H, where one member is in a position of structural power, disagreement takes over the group. Once the evaluation distance increases above 5, the majority of the behavior of the group is categorized as disagreement, tension and antagonism. This finding suggests that groups with members of distance in status greater than 5 do not collaborate well together, as the behavior dynamics are overwhelmingly negative. An evaluation distance of 5 is incredibly uncommon, perceivably because of this predicted result, but also given the positive bias of identity values in society. For collaborative task groups, an evaluation distance approximately spans a range of 0 to 3.

While Figure 4.3 suggests the importance of status difference in groups, only the range of evaluation distances from 0 to 3 are representative of collaborative task groups. Within this range, Figure 4.3 shows that when certain group members are perceived as fundamentally bad, or even fundamentally neutral (when both E values are set to 0 at E distance 0), a large amount of negative socio-emotive behavior is experienced. According to Bales' theories about how IPA categories impact collaborative task groups, groups must have more positive socio-emotive behaviors than negative socio-emotive behaviors for effective task accomplishment (Bales 1970). Figure 4.3 shows that with these evaluation identity values, these groups would not have effective task accomplishment. The negative socio-emotive behavior present exceeds the suggested limit of 30% that Bales found (Bales 1999). Perhaps, when group members are perceived as fundamentally bad or even with evaluation values of 0, fundamentally neutral, tension and disagreement develop within a group and the group is ineffective.

In order to further examine these findings and the potential implications for collaborative task groups, I explore differences in only positive evaluation values in section 4.4. In Figure 4.5, I examine the variation in behavior dynamics as the potency distance increases.

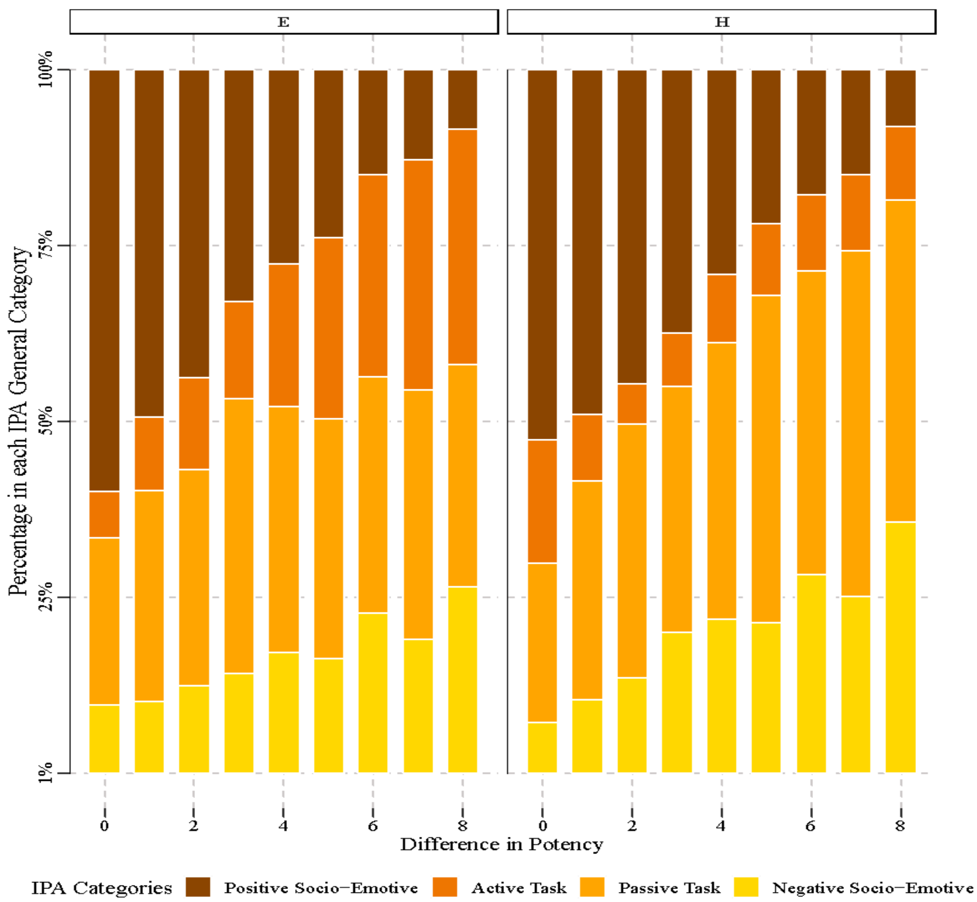


Figure 4.5 IPA Categories for Potency Gradient from P = -4 to P = 4, Network structures are represented by the two columns, E for egalitarian and H for hierarchical.

Figure 4.5 shows group behaviors are distributed across IPA categories as the potency distance between agents increases, using the definitions of potency distance specified in Table 4.2. The plot shows increasing negative socio-emotive behavior and decreasing positive socio-emotive behavior as the difference in potency between agents increases. Task-related behaviors comprise a larger share of group dynamics, and socio-emotive behaviors a smaller share as potency distance increases. These patterns are fairly stable across both network structures. Bales found that groups must have more positive socio-emotive behaviors than negative socio-emotive behaviors for effective task accomplishment (Bales 1970). Figure 4.5 shows that this balance exists for groups with a potency distance of less than 5, but negative socio-emotive behavior exceeds positive socio-emotive behavior thereafter.

While low levels of potency distance (0-1) show to similar levels of active and passive task behavior across network structures, distinct patterns of task behavior emerge by network type as the potency distance increases. In the hierarchical group structure, active task behaviors remain relatively constant while passive task behavior increases as the potency distance increases. In the egalitarian group structure, active task behavior comprises an increasing share of overall group behavior as the potency distance increases. The increase in active task in the egalitarian group with large potency distances might suggest that the hierarchy imposed by the potency disparities allows for the group to increase task contribution. As these potency distances are outside of the range common to collaborative task groups, I did not further explore this trend and this idea should be further examined in future research.

As with the evaluation distances present in collaborative task groups on GitHub, it is very uncommon to find potency distances of greater than 3 between group members. As you can imagine from the example of employer and intern identities as having a potency distance of 2, much larger potency distances are uncommon. Over the range of low potency distance, the groups experience significant positive socio-emotive behavior but limited active task behavior. While groups with power disparities in these network structures are not experiencing much negative socio-emotive behavior, they still are not very productive as active task makes up less than 10% of the behavior. In order to observe if this is a result of negative potency values constraining the group by causing problems in group dynamics, I explore differences in only positive potency values in section 4.4.

Figure 4.5 illustrates that while group structure does impact the behavior produced in groups over the gradient of potency distance, group structure impacts behavior less over the potency gradient than over the evaluation gradient illustrated in Figure 4.4. Therefore, network structure influences group behavior more over differences in the status of group members than differences in the power of group members.

4.4 How Positive Evaluation and Potency Gradients Impact Behavior Dynamics

The evaluation and potency gradients examined so far have ranged from -4 to +4, centered around the value of 0. To observe the significance of a 0 threshold, which reflects a perceptual shift in viewing a given agent as fundamentally good or bad, powerful or powerless, Figure 4.6 and Figure 4.7 examine differences in evaluation and potency from 0 to +2, centered around the value of +1. The differences were observed at increments of 0.2. Table 4.3 shows the negative and positive evaluation gradients used to observe the 0 threshold in Figure 4.6. Figure 4.6 and Figure 4.7 use IPA categories to explore the impact on behavior dynamics.

	Negative Gradient		Positive Gradient				
E Distance	**Agent 1: E**	**Agents 2&3: E**	**Agent 1: E**	**Agents 2&3: E**	**P**	**A**	**Address to Group**
0	0	0	1.0	1.0	1	1	0.4
0.2	0.1	-0.1	1.1	0.9	1	1	0.4
0.4	0.2	-0.2	1.2	0.8	1	1	0.4
0.6	0.3	-0.3	1.3	0.7	1	1	0.4
0.8	0.4	-0.4	1.4	0.6	1	1	0.4
1.0	0.5	-0.5	1.5	0.5	1	1	0.4
1.2	0.6	-0.6	1.6	0.4	1	1	0.4
1.4	0.7	-0.7	1.7	0.3	1	1	0.4
1.6	0.8	-0.8	1.8	0.2	1	1	0.4
1.8	0.9	-0.9	1.9	0.1	1	1	0.4
2.0	1.0	-1.0	2.0	0	1	1	0.4

Table 4.3 Identity values selected to represent positive and negative gradients of evaluation distance in increments of 0.2 (+0.1 to Agent 1 and -0.1 to Agents 2 and 3 for each step) while holding the address to group rate constant at 0.4.

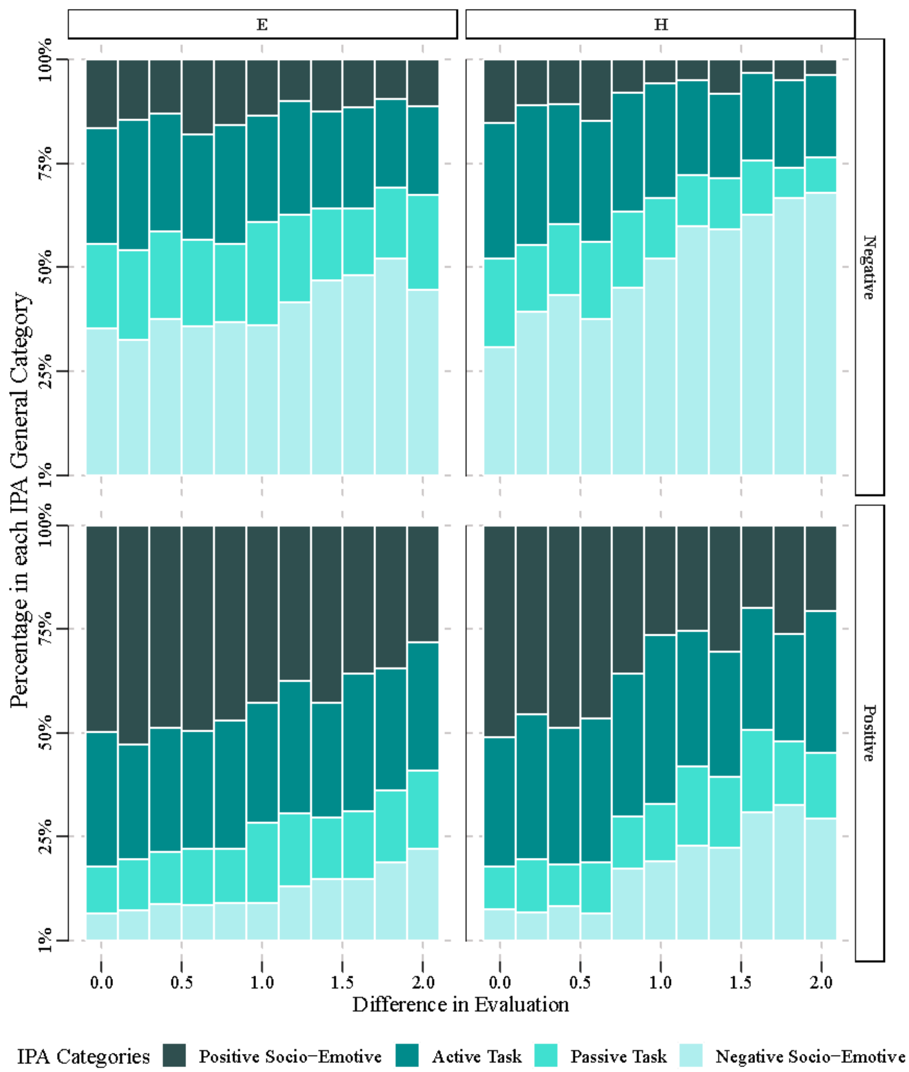


Figure 4.6 IPA Categories comparing negative evaluation gradient, from E = -1 to E = 1, with positive evaluation gradient, from E = 0 to E = 2, to show importance of 0 threshold

Figure 4.6 shows the IPA categories of behavior produced for simulations with evaluation values centered around 0 (negative gradient) and centered around 1 (positive gradient). While the negative gradient for evaluation shows, at a minimum, 30% negative socio-emotive behavior, the positive gradient shows a greater presence of the other three categories of behavior. The positive evaluation gradient reveals a 50% presence of positive socio-emotive behavior, which decreases as the gradient increases. Active task behavior remains constant, while passive task behavior increases slightly as the evaluation difference increases. Negative socio-emotive behavior increases at a similar rate to the decreasing positive socio-emotive behavior. The positive evaluation gradient is less impacted by group structure than the negative evaluation gradient.

Figure 4.6 suggests that the perceptual shift in viewing a group member as fundamentally good or bad disrupts the behavior dynamics of the group. When all members of the group are considered fundamentally good, much less negative socio-emotive behavior is produced and there is an increase in positive socio-emotive behavior relative to groups in which some members are fundamentally good while others are fundamentally bad. According to Bales, the suggested upper limit of negative socio-emotive behavior in an effective task group is 30%. Figure 4.6 shows that in groups with evaluation distances that span negative evaluation values, all of the simulated groups are predicted to experience socio-emotive behavior that is more than 30% negative. However, in the positive gradient of evaluation distance, negative socio-emotive behavior only rises to 25% when the evaluation distance increases to 2. My findings suggest that collaborative task groups in which all members are perceived as good experience similar levels of task behavior, but significantly more positive socio-emotive behavior and less negative socio-emotive behavior. This predicts that groups with all fundamentally good members will have increased group efficacy, an important implication for collaborative task groups.

Table 4.4 shows the identity values used for Figure 4.7.

		Negative Gradient		**Positive Gradient**			
P Distance	**E**	**Agent 1: P**	**Agents 2&3: P**	**Agent 1: P**	**Agents 2&3: P**	**A**	**Address to Group**
0	1	0	0	1.0	1.0	1	0.4
0.2	1	0.1	-0.1	1.1	0.9	1	0.4
0.4	1	0.2	-0.2	1.2	0.8	1	0.4
0.6	1	0.3	-0.3	1.3	0.7	1	0.4
0.8	1	0.4	-0.4	1.4	0.6	1	0.4
1.0	1	0.5	-0.5	1.5	0.5	1	0.4
1.2	1	0.6	-0.6	1.6	0.4	1	0.4
1.4	1	0.7	-0.7	1.7	0.3	1	0.4
1.6	1	0.8	-0.8	1.8	0.2	1	0.4
1.8	1	0.9	-0.9	1.9	0.1	1	0.4
2.0	1	1.0	-1.0	2.0	0	1	0.4

Table 4.4 Identity values selected to represent positive and negative gradients of potency distance in increments of 0.2 (+0.1 to Agent 1 and -0.1 to Agents 2 and 3 for each step) while holding the address to group rate constant at 0.4.

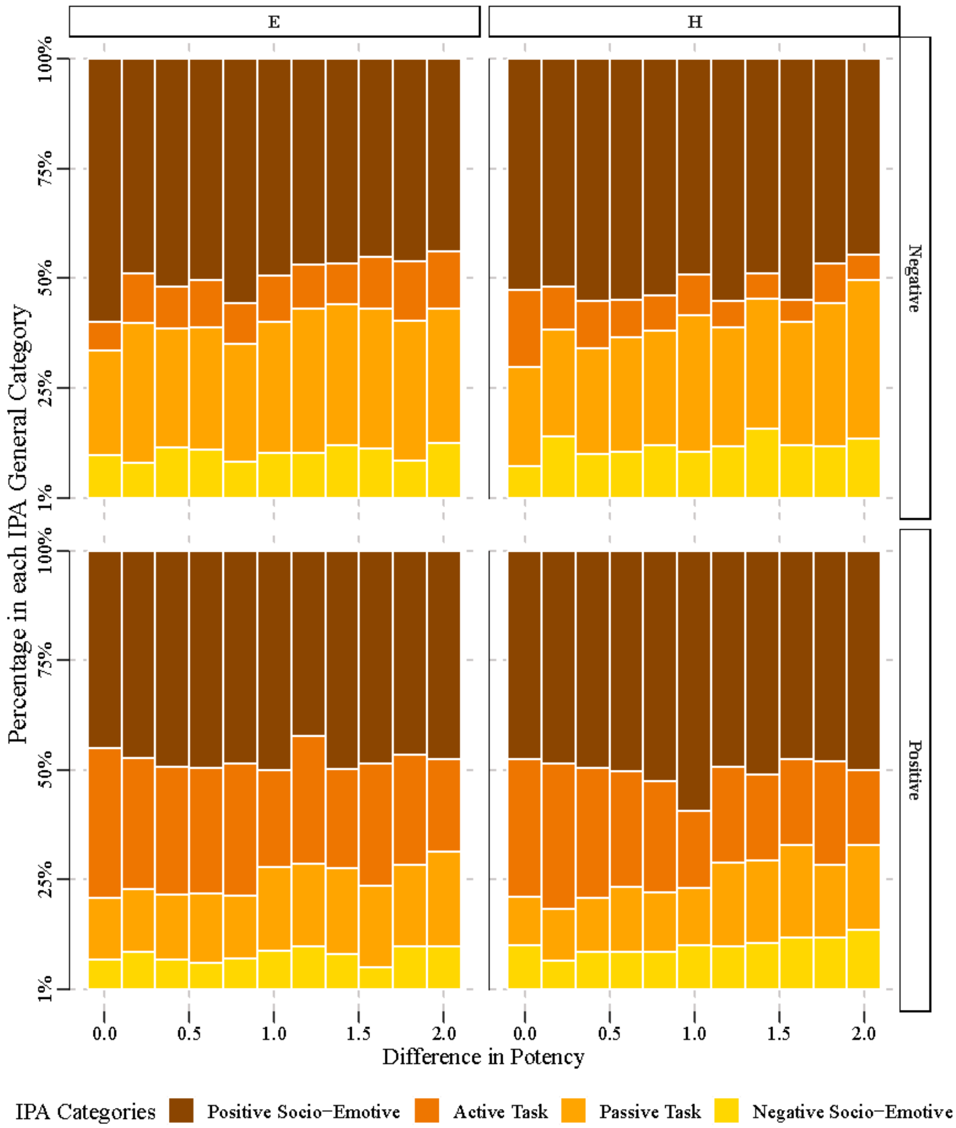


Figure 4.7 IPA Categories comparing negative potency gradient, from P = -1 to P = 1, with positive evaluation gradient, from P = 0 to P = 2, to show importance of 0 threshold

Figure 4.7 shows the IPA categories of behavior produced for simulations with potency values ranging from -1 to 1 and potency values ranging from 0 to 2. In the positive gradient, positive socio-emotive behavior fluctuates slightly but is almost constant across changes in potency. Negative socio-emotive behavior increases slightly in the hierarchical group structure but does not greatly impact the behavior produced over the gradients in the network structure.

According to Bales' findings on effective task groups (Bales 1999), all of the groups in Figure 4.7 would have effective task accomplishment as the predicted positive socio-emotive behavior is greater than the negative socio-emotive behavior. However, the groups with positive potency values are predicted to have active task behavior values much closer to the suggested limits. Active task limits are suggested to be between 37% and 81%. While few of these groups show such values of active task that even reach the lower limit, the positive gradient includes much more active task. For both network structures, active task behavior decreases as passive task behavior increases. In the positive gradient, the groups experience more task behavior relative to the negative gradient. This suggests that in groups with all fundamentally strong members, more active task behavior is experienced and therefore the group would experience more effective task accomplishment and have increased efficacy.

Figure 4.6 and Figure 4.7 suggest that the zero threshold of evaluation and potency distance impact behavior dynamics by improving the group task efficiency. These findings suggest that the perceptual shift in viewing a given group member as fundamentally good or bad or viewing a given group member as fundamentally strong or weak is an important contributor to group efficacy. My findings predict interesting intersections of the hierarchies of network structure and cultural sentiments which advance existing theory on group dynamics in online collaborative task groups. In Chapter 5, I go through these findings and the implications of my results.

Chapter 5 - Discussion

In this chapter, I begin by summarizing my findings on the factors predicting success and those predicting disruption for collaborative task groups, which I examined in greater detail in Chapter 4. Next, I discuss the implications my results have for collaborative task groups and theorize as to how teams on GitHub can improve group efficacy and longevity. I also explore what my findings suggest beyond the scope of collaborative task groups about the longstanding inequalities that exist in our society. Finally, I examine the limitations of my research design and conclude by sharing the opportunities that these limitations and my model provide for future research.

5.1 Summary of Research and Findings

My findings reveal how hierarchies of network structure and cultural sentiments interact to shape affective alignment and behavior dynamics in collaborative task groups. My results predict that group members experience different amounts of tension due to violated expectations depending on their role within the group. Increasing differences in evaluation (status, respect, esteem) and potency (power, control, authority) cause problems for group dynamics and behavior, and status differences disrupt group dynamics more than power differences.

First, I examined the predicted tension and uneasiness experienced by each role within the group. I found that the group member with high relative structural authority and cultural sentiments denoted by respect or power, experiences increasing violation of their expectations, relative to other group members, as the evaluation and potency distance increases. This finding advances previous literature that has focused primarily on individual level factors in groups. My sociological simulation-based approach to predict these patterns emphasizes the contextual effects of role composition. Prior research has observed that a person experiences more deflection when acted upon by a member with equal power than a member with a more potent identity (Morgan et al. 2016). My findings support this observation and examine the experiences of both the members with the more potent identity and the less potent identity, and also observe the impact of status differences on deflection experienced by members of a group. The US impression formation equations reveal a principle of impression formation that is reflected in these findings: respected actors are expected to act nicely unless they are interacting with a bad person. Then, good people should direct negative actions at bad people. For example, a hero (high status or respect) is expected to direct negative actions at a villain (low status or respect). However, when a hero performs a negative action, this action results in a violation of their expectations, as they expect themselves, as a hero, to perform positive actions. While heroes and villains may not be found in collaborative task groups, this example represents an interaction between group members with varying identities of respect or status. The finding has interesting implications for members of collaborative task groups.

Second, my findings predict that status hierarchies and power hierarchies including negative evaluation and potency values cause problems for group dynamics. Group dynamics are significantly disrupted in groups with members whose identity differences span negative and positive values (i.e., one member of the group is fundamentally good while others are fundamentally bad, or one member of the group is fundamentally strong while others are fundamentally weak). Not only do my findings suggest that there is significant tension in these groups due to group members' expectations being violated, but also overwhelming disagreement and low levels of task behavior. My findings support and expand upon previous research about group dynamics and online collaborative teams that focused on factors that contribute to the success of individual team members (Ducheneaut 2005, Tsay et al. 2014, Rastogi et al. 2016, Rishi 2017). My findings particularly expand upon the limited research that has considered both the meanings of the identities that define a culture and the impact of relational norms. My findings suggest that a hierarchical network structure helps mitigate some of the disruption to group dynamics with power and status disparities. These findings support previous research suggesting that members of hierarchical groups experience lower levels of uncertainty given their explicit roles in the group while members of egalitarian groups expect themselves to be treated as equals and therefore experience higher levels of affective misalignment as the objects of others' behavior (Morgan, Rogers, and Hu 2016, Morgan et al. 2019). As this object diminishment effect has been observed through the lenses of structural hierarchy and power hierarchies in the past, my findings expand this finding to status hierarchies.

Third, my findings suggest that status differences within groups disrupt group dynamics more than power differences. Status differences impact both the tension experienced by group members and the behavior produced in their interactions. The finding that group members with status differences experience increasing tension due to a violation of their expectations expands on the principle of impression formation that respected actors are expected to act nicely unless they are interacting with a bad person. The tension a person experiences due to their expectations being violated is based on both their feelings about their own actions and the resulting feeling of being acted upon. When a strong person is acted upon by a weak person or a respected person is acted upon by a disrespected person, they experience deflection. While a strong person is expected to act in a display of strength, doing so towards group members who are weak does not greatly disrupt their identity, thereby not violating their expectations. However, a respected person is expected to act badly towards disrespected people, which violates their perception of themselves as a good person who is expected to act nicely. This finding advances previous literature by emphasizing the contextual effects of group structure and by applying an identity maintenance perspective.

While previous literature has examined the operation and maintenance of hierarchy formation in groups (Skvoretz 1988), there are few generative models of these dynamics (Ridgeway and Balkwell 1997). My findings provide a unique extension of previous literature as Group Simulator is the first model, to my knowledge, that allows for simultaneous modeling of network structures and identity maintenance / cultural factors in the same simulation model. My findings are based on a theoretically grounded, simulation-based model that is predictive of future behavior. The model provides scalable predictions, which allow us to better understand variations based on several group characteristics at once and the interactions of their effects. These findings about the relationship between group characteristics and group outcomes suggest avenues for additional research and can be validated against data scraped from GitHub in the future.

5.2 Implications

My findings indicate three main implications for collaborative task groups. First, structure and culture have real consequences for collaborative task groups. Second, fundamentally bad or weak group members disrupt group dynamics. Third, the group leader experiences the most disruption. In this section I begin by elaborating on the importance of these implications for collaborative task groups. Next, I share my predictions of how collaborative task groups can be improved. Finally, I suggest how my findings provide meaningful insight into group interactions and group dynamics beyond task groups.

My findings suggest that network structure and culture have real consequences for group dynamics in collaborative task groups. Groups with members who are fundamentally bad or fundamentally weak experience high levels of negative socio-emotive behavior (disagreement), which limit the group from experiencing task behaviors, therefore inhibiting their task performance. Low task performance results in low group efficacy as the group is not able to be productive or efficient. These groups also experience high levels of deflection (tension due to violated expectations). Affect Control Theory (ACT) argues that persistent deflection can encourage people to exit interactions when strategies such as redefining the situation or utilizing behavioral remedies are unsuccessful. Therefore, the increasing deflection experienced by members of the group threatens member retention and group longevity. These findings have important implications for both the group as a whole and the individuals in the group. For example, a task group that is paid based on productivity is challenged as group members who cannot perform their identities cannot transfer capital. Not only is the group inhibited, but the person of higher status or power in the group is predicted to experience the most tension and unease. This group member, who is likely to hold the role of group leader, experiences consequences for status attainment. As performance declines, so do salary and promotion opportunities. When network structures and role performances constrain the optimization of identity, task groups are not able to be successful.

By applying an understanding of group process according to Bales and other previous literature, my findings suggest that the two hierarchies observed in my simulations can greatly contribute to the success of task groups. My findings suggest that optimal collaborative task groups should include low levels of potency and evaluation distance spanning only positive evaluation and potency values, and function in hierarchical network structures. These structures will allow groups to experience less tension due to group members' expectations being violated, less disagreement (negative socio-emotive behavior), and greater levels of active task behavior, which increase group productivity (Bales 1999). With lower levels of deflection, members are not encouraged to exit the situation so member retention increases and group longevity improves. With the expansion of task behavior and the contraction of negative socio-emotive behavior, task related outcomes improve, thereby increasing group efficacy. Therefore, collaborative task groups with members of similar status and power who are fundamentally good and strong and interact in a hierarchical network structure will experience improved group longevity and efficacy.

These predictions can provide insight into current team dynamics and probable causes for experienced tension, can be used as guidance for the formation of new teams, and can be used as an awareness factor when constructing a GitHub identity profile. These predictions enable collaborative groups to build teams that include factors likely to contribute to their success, leading to improved performance, and consequentially salary and promotion benefits. When constructing a GitHub identity profile, a software developer can take these suggestions into consideration when deciding what information to include in order to shape their task-related identity.

Beyond the scope of task groups, I observe ways in which my findings could have interesting implications regarding the longstanding inequalities that exist in our society. For example, my results suggest that a person of higher power feels unease when a person of lower power acts on them. According to the Interact dictionary of EPA values compiled through empirical study, the identity "man" has a much greater potency level than the identity "woman" (Heise 1997). Therefore, my findings suggest that given the current definitions of identity meaning, men feel tension when acted upon by women. Throughout the dictionary, identities of varying race, class, sexual orientation, and gender have power and status disparities. My findings call into question how status and power are manufactured in our society and how current hiring and promotion practices may be influenced by existing status and power disparities. As my findings were limited to observing the scope of collaborative task groups, these observations suggest areas of important future research.

5.3 Limitations

When examining the limitations of my work, it is important to consider how my findings are hypotheses that can be validated with data from GitHub in the future. As I used an agent-based model to simulate group interactions, my findings suggest avenues for future work and validation.

The scope of my findings is limited to collectively oriented and task-oriented groups, as my research design was structured to match interaction methods for software development teams on GitHub. My work focuses only on studying interactions among groups of English speakers. The dictionaries and impression dynamics equations used in these simulations are limited to United States English speakers. Therefore, my results summarize fundamental sentiments for identities and behaviors among U.S. English speakers. Another limitation I faced with the use of the Interact and GitHub dictionaries is a strong positive bias. Though collected through empirical studies, the dictionaries include mainly positive identity values, which make negative values increasingly bad, weak or inactive very quickly and reflect society's preference for positive identity values. As the GitHub dictionary is even more positively skewed through the positive self-identification bias that existed when it was created, my ability to fully explore differences in identities on GitHub is limited to mainly positive identity values.

My research questions focused on the interactions of hierarchies. Therefore, I focus on only two of the dimensions of ACT: evaluation and potency. A limitation of my model is from holding the third dimension, activity, constant at a value of 1.0. Activity is a constant in my simulations, but activity values can vary along with evaluation and potency for identities in the Interact and GitHub dictionaries. Another limitation of my research design includes the assignment of an increasing evaluation or potency value to a single agent in the group. In my simulations, I set Agent 1 as the agent in a position of structural power according to the network structure, and also set Agent 1 as the agent with increasing evaluation or potency identity values while Agent 2 and Agent 3 had decreasing evaluation or potency identity values. With this assignment, my findings are limited to groups in which structural and cultural hierarchies aligned.

Additionally, I used two network structures in my simulations, but there are five identified network structures on GitHub. Therefore, my findings are limited to the most egalitarian and most hierarchical network structures on GitHub. An opportunity for future research would be to explore the influences of the three other more complex network structures that exist on GitHub on the affective alignment and behavior in the collaborative task groups.

Group Simulator is a recent advancement of the Interact model and therefore presents several limitations that can be advanced with future work. Group interactions on Group Simulator can range from group size of three to twenty-five. Given the single line of exchanges, Group Simulator cannot simulate the multiple foci of interaction common in larger groups (Heise 2013). Groups of twenty-five members on Group Simulator interact with an imposed one-at-a-time principle, similar to classroom discussions. As structural constraints of this sort are only imposed in some interactions on GitHub, my study focuses on small-groups, particularly triads. Therefore, restricting to three agents is a limitation and there is potential to scale the network to model larger group interactions in the future.

5.4 Future Research

There are many opportunities for future research on the intersecting effects of hierarchies of structure and culture on group dynamics. Group Simulator is a recent advancement of previous models and a recent extension of ACT to model group interactions. Limitations such as the imposed single-line interaction could be further advanced in the model. Group Simulator could also be used to scale the classic ACT group model to the more recent generalization of ACT, BayesACT.

In my work, I explore evaluation and potency because of their relationships with the sentiments of status and power, but the third dimension used to quantify affect in ACT, activity, could be further explored. I hold activity and either evaluation or potency constant at the value of 1.0 to observe evaluation or potency distance. Future work could hold the two dimensions that are not being varied constant at different values to see if my findings hold as the dimensions becomes more positive or negative. Distances of the activity dimensions could also be explored to see if differences in group member contribution levels contribute to group dynamics.

I observe interactions in which structural and cultural hierarchies align. An opportunity for future research would be to invert these hierarchies, giving the structurally advantaged actors lower evaluation and potency, and the structurally disadvantaged actors higher evaluation and potency identity values. This would be an interesting case study of the circumstances under which conflicting information could potentially challenge the legitimacy of actors in positions of structural power. Another opportunity for future research would be to keep the structural hierarchies used in this work, but to assign the position of increasing cultural status or power to either Agent 2 or 3. This method would also challenge the legitimacy of actors in positions of structural power and might uncover some interesting interaction dynamics between Agent 2 and Agent 3, agents with equal structural power but varying cultural identity meanings.

As our world transitions to an emerging distributed economy and digital democracy, understanding the factors that contribute to group efficacy and longevity is becoming increasingly important. This research observes how affective dynamics as well as socio-emotive and task-related behavior are shaped by hierarchies of network structure and cultural sentiments such as status and power. This work suggests important implications as to the role of respect and power on group dynamics. As the recent extension of Group Simulator is the first model to allow simultaneous modeling of network structures and identity maintenance / cultural factors, this work provides a starting point for future research to further examine and seek to understand the dynamics of online collaborative task groups.

References

Akerlof, G.A., Kranton., R.E. 2000. “Economics and identity.” Quarterly Journal of Economics (115): 715-53.

Akerlof, G. A., Kranton., R.E. 2010. "A Rosetta Stone." Identity Economics: How Our Identities Shape Our Work, Wages, and Well-Being, 21-26. Princeton, New Jersey; Woodstock, Oxfordshire: Princeton University Press.

Alhothali, A. and Hoey, J. 2015. “Good news or bad news: Using affect control theory to analyze readers reaction towards news articles.” Proc. Conf. NAACL HLT, Denver, CO.

Ambrasat, J., von Scheve, C., Conrad, M., Schauenburg, G., & Schröder, T. 2014. “Consensus and stratification in the affective meaning of human sociality.” Proc. National Academy of Sciences of the United States of America, 111 (22), 8001–6.

Bales, R. F. 1950. “Interaction Process Analysis: A Method for Studying Small Groups.” Cambridge, Mass: Addison-Wesley.

Bales, R. F. 1970. “Personality and Interpersonal Behavior.” New York: Holt, Rinehart.

Bales, R. F. 1999. “Social interaction systems: Theory and measurement.” Transaction.

Bales, R. F. 2000. “Social Interaction Systems: Theory and Measurement: Book Review.” Group Dynamics: Theory, Research, and Practice 4 (2): 199–208.

Benkler, Y. 2006. The Wealth of Networks. Yale University Press,

Berger, J., Conner, T. and Fisek, M. H. 1974. “Expectation States Theory: A Theoretical Research Program.” Cambridge, Mass.: Winthrop.

Berger, J. 2014. “Word of mouth and interpersonal communication: A review and directions for future research.” Journal of Consumer Psychology (24): 586–607.

Bogers, M. and West, J. 2012. “Managing distributed innovation: Strategic utilization of open and user innovation.” Creativity, Innovation, and Management (21): 61-75.

Blowfield, M., Johnson, L. 2013. “Turnaround challenge: Business and the city of the future.” Oxford University Press.

Burke, P. 1967. “The Development of Task and Social-Emotional Role Differentiation.” Sociometry 30(4): 379-392.

Burt, R. 2002. "The social capital of structural holes." The new economic sociology: Developments in an emerging field 148.

Cohen, N. 2018. “After years of abusive emails, the creator of Linux steps aside.” The New Yorker.

Coleman, J. 1994. Foundations of Social Theory. Harvard University Press.

Dabbish, L., Stuart, S., Tsay, J, Herbsleb, J. 2012. “Social coding in GitHub: Transparency and collaboration in an open software repository”. Proc. ACM-CSCW 2012, 1277-86.

Daniel, S. L., Maruping, L. M., Cataldo, M., Herbsleb, J. (2018). “The impact of ideology misfit on open source software communities and companies.” MIS Quarterly 42(4): 1069-1096.

Ducheneaut, N. 2005. “Socialization in an Open Source Software Community: A Socio-Technical Analysis.” Computer Supported Cooperative Work (14): 323–368.

Fielding, K.S., McDonald, R., and Louis, W.R. 2008. “Theory of planned behavior, identity, and intentions to engage in environmental activism.” Journal of Environmental Psychology 28, 318-26.

Francis, C. and Heise, D.R. 2006. ‘‘Mean Affective Ratings of 1,500 Concepts by Indiana University Undergraduates in 2002-3.’’ http://www.indiana.edu/~socpsy/ACT/inter act/JavaInteract.html).

Gibson, D. R. 2010. “Marking the turn: Obligation, engagement, and alienation in group discussions.” Social Psychology Quarterly 73(2): 132-151.

GitHub. “About.” Last accessed April 2020. https://github.com

Glorot, X., Bordes, A., and Bengio, Y. 2011. “Domain adaptation for large-scale sentiment classification: A deep learning approach.” Proc. 28th Int. Conf. Machine Learning, Bellevue, WA, USA.

Gutwin, C., Penner, R., and Schneider, K. 2004. “Group awareness in distributed software development.” Proc. CSCW, ACM: 72-81.

Gratch, J., Cheng, L., & Marsella, S. 2015. “The appraisal equivalence hypothesis: verifying the domain-independence of a computational model of emotion dynamics.” 2015 international conference on affective computing and intelligent interaction (ACII): 105–111. IEEE.

Gratch, J. & Marsella, S. 2004. “A domain-independent framework for modeling emotion.” Cognitive Systems Research, 5(4): 269–306.

Healy, L. Schussman, A. 2003. “The ecology of open-source software development.” Technical Report, University of Arizona.

Heise, D.R. 1997. INTERACT computer model of social interaction, Java archive, http://www.indiana.edu/~socpsy/ACT/interact.htm, last accessed 2019/04/30.

Heise, D.R. 2007. “Expressive order: Confirming sentiments in social actions.” Springer.

Heise, D.R. 2013. GroupSimulator, model code and documentation/ user manual, http://www.indiana.edu/~socpsy/ACT/SmallGroups/GroupSimulator.html, last accessed 2020/01/30.

Heise, D.R. 2013. “Modeling interactions in small groups.” Social Psychology Quarterly 76(1), 52- 72.

Heise, D.R., and Lerner, S.J. 2006. “Affect control in international interactions”. Social Forces 85(2), 993-1010.

Helbing, D. and Pournaras, E. 2015. “Build digital democracy.” Nature, 527, 33-34.

Hochschild, A. R. 1983. “The managed heart: commercialization of human feeling.” Berkeley, University of California Press.

Hoey, J., Schröder, T., and Alhothali, A. 2013. “Bayesian affect control theory.” In Proc. of International Conference on Affective Computing and Intelligent Interaction.

Hoey, J., Schröder, T., Alhothali, A. 2016. “Affect control processes: Intelligent affective interaction using a partially observable Markov decision process.” Artificial Intelligence 230, 134-72.

Hoey, J., Schröder, T., Morgan, J.H., Rogers, K.B., Rishi, D., Nagappan, M. 2018. “Artificial intelligence and social simulation:

Studying group dynamics on a massive scale." Small Group Research 49(6), 647–683.

Hofstede, G.J. 2017. "GRASP agents: Social first, intelligent later." AI & Society: 1-9.

Katz, N., Lazer, D., Arrow, H., Contractor, N. 2004. "Network theory and small groups." Small Group Research (35): 307-32.

Kajiç, I., Schröder, T., Stewart, T.C., Thagard, P. 2019. "The Semantic Pointer Theory of Emotion: Integrating Physiology, Appraisal, and Construction", Cognitive Systems Research.

Kemper, T. D. 2006. "Power and status and the power-status theory of emotions." Handbook of the sociology of emotions: 87-113. Springer.

Kinnvall, C. 2004. "Globalization and religious nationalism: Self, identity, and the search for ontological security." Political Psychology 25, 741-67.

Klandermans, P. G. 2014. "Identity Politics and Politicized Identities: Identity Processes and the Dynamics of Protest." *Political Psychology* 35, no. 1: 1-22.

Krackhardt, D. 1999. "The Ties that Torture: Simmelian Tie Analysis in Organizations." Research in the Sociology of Organizations (16), 183-210.

Lin, N. 1999. "Social Networks and Status Attainment." Annual Review of Sociology 25(1): 467-487.

Luther, K. Caine, K. Ziegler, K. Bruckman, A. 2010. "Why It Works (When It Works): Success Factors in Online Creative Collaboration)". ACM International Conference on Supporting Group Work (16): 1-10.

Machkovech, S. 2015. "Linus Torvalds on why he isn't nice: 'I don't care about you.'" Ars Technica.

MacKinnon, N.J. and Heise, D.R. 2010. "Self, identity, and social institutions." NYC: Palgrave Macmillan.

Mäntylä, M., Adams, B., Destefanis, G., Graziotin, D., Ortu, M. 2016. "Mining valence, arousal, and dominance: possibilities for detecting burnout and productivity?" Proc. MSR 2016, 247-258.

Marlow, J., Dabbish, L., Herbsleb, J. 2013. "Impression formation in online peer production: Activity traces and persona profiles in Github." Proc. Conf. Computer Supported Cooperative Work, 117-128.

Mead, G.H. 1938. "The Philosophy of the Act." Chicago: The University of Chicago Press.

Miles, A. 2015. "The (re)genesis of values: Examining the importance of values for action." American Sociology Review 80, 680-704.

Miller, D. 2007. "Dyad/Triad." The Blackwell Encyclopedia of Sociology, 1-4.

Moody, G. 2001. "Rebel code: Linux and the open source revolution." New York: Perseus.

Morgan, J., Zhao, J., Sedlacek, A., Chen, L., Piper, H., Beck, Y., Rogers, K. 2019. "Modeling the Culture of Online Collaborative Groups with Affect Control Theory." Social Simulation Conference, Mainz, Germany, Sept 2019.

Nakov, P., Zesch, T., Cer, D., and Jurgens, D. 2015. International Workshop on Semantic Evaluation (9).

Olmsted, Michael S. 1954. "Orientation and Role in the Small Group." *American Sociological Review* 19, no. 6: 741-51.

Ortu, M., Adams, B., Destefanis, G., Tourani, P., Marchesi, M., Tonelli. R. 2015. “Are bullies more productive? Empirical study of affectiveness vs. issue fixing time.” Proc. MSR 2015, 303-313.

Osgood, C. E., May, W. H., and Miron, M. S. 1975. “Cross-cultural universals of affective meaning.” University of Illinois Press.

Osgood, C. E., Suci, G. J., & Tannenbaum, P. H. 1957. “The measurement of meaning.” University of Illinois Press.

Pang, B., Lee, L., Vaithyanathan, S. 2002. “Thumbs up? Sentiment classification using machine learning techniques.” Proc. ACL-02 Conference on Empirical Methods in Natural Language Processing, 79–86.

Polley, R.B., Hare, A.R. Stone, P.J. 1988. “The SYMLOG practitioner: Applications of Small Group Research.” New York: Praeger.

Rastogi, A., Nagappan, N., Gousios, G. 2016. “All contributors are equal; Some contributors are more equal than others.” IIITD-TR-2016-001.

Reisenzein, R., Hudlicka, E., Dastani, M., Gratch, J., Hindriks, K., Lorini, E., Meyer, J.-J. C. 2013. “Computational modeling of emotion: toward improving the inter- and intradisciplinary exchange.” IEEE Transactions on Affective Computing, 4(3), 246–266.

Ridgeway, C.L. and Balkwell, J. W. 1997. “Group processes and the diffusion of status beliefs.” Social Psychology Quarterly 60(1): 14-31.

Ridgeway, C., and Johnson, C. 1990. “What Is the Relationship Between Socioemotional Behavior and Status in Task Groups?” American Journal of Sociology, 95(5), 1189-1212.

Rishi, D. 2017. “Affective Sentiment and Emotional Analysis of Pull Request Comments on GitHub.” UWSpace.

Robinson, D.T. and Smith-Lovin, L. 1992. “Selective interaction as a strategy for identity maintenance: An affect control model.” Social Psychology Quarterly 55(1), 12-28.

Robinson, D., Smith-Lovin, L., and Wisecup, A. 2006. “Affect Control Theory.” Handbook of the Sociology of Emotions.

Schneider, A. and Schröder, T. 2012. “Ideal Types of Leadership as Patterns of Affective Meaning: A Cross-cultural and Over-time Perspective.” Social Psychology Quarterly 75(3): 269-287.

Schröder, T. and Scholl, W. 2009. “Affective dynamics of leadership: An experimental test of Affect Control Theory.” Social Psychology Quarterly 72(2), 180-197.

Schröder, T., Hoey, J., and Rogers, K.B. 2016. “Modeling dynamic identities and uncertainty in social interaction: Bayesian affect control theory.” American Sociological Review 81(4), 828-855.

Skvoretz, J. 1988. Models of participation in status-differentiated groups. Social Psychology Quarterly 51(1): 43-57.

Simmel, G. 1950. “Individual and Society.” The Sociology of Georg Simmel, edited by K.H. Wolff. New York: Free Press.

Slater, Phillip E. 1955. "Role Differentiation in Small Groups." American Sociological Review 20: 300-310.

Snedecor, G. W. 1946. “Statistical Methods.” Iowa State College Press (4).

Socher, R., Perelygin, A., Wu, J.Y., Chuang, J., Manning, C.D., Ng, A.Y., Potts, C. 2013. “Recursive deep models for semantic compositionality over a sentiment treebank.” Proc. Conference on empirical methods in natural language processing (EMNLP) 1631, 1642-1654.

Strodtbeck, F. L., James, R. M., Hawkins, C. 1957. “Social status in jury deliberations.” American Sociological Review 22(6): 713-719.

Strodtbeck, F. L., Hare, A. P. 1954. “Bibliography of small group research (from 1900 through 1953).” Sociometry 17(2): 107-178.

Squazzoni, F. 2012. “Agent-based computational sociology.” Wiley.

SCG. “What is SYMLOG?” Last accessed May 2020. https://www.symlog.com/SYMLOG/WhatIsSYMLOG.aspx

THEMIS.COG. “Home.” Last accessed March, 2020. https://themis-cog.github.io/#

Townsend, A.M. 2013. “Smart cities: Big data, civic hackers, and the quest for a new utopia.” Norton.

Tsay, J., Dabbish, L., and Herbsleb, J. 2014. “Influence of social and technical factors for evaluating contribution in GitHub.” Proc. 36th International Conference on Software Engineering, 356-366.

Turney, P., and Littman, M. 2007. “Unsupervised learning of semantic orientation from a hundred billion-word corpus.” NRC TR.1094.

Vasilescu, B., Posnett, D., Ray, B., van den Brand, M.G.J., Serebrenik, A., Devanbu, P., and Filkov, V. 2015. “Gender and tenure diversity in GitHub teams.” Proc. 33rd ACM CHI, 3789-98.

Verba, S. 1961. “Small Groups and Political Behavior.” New Jersey: Princeton University Press.

Von Scheve, C. 2014. “Emotion and social structures: the affective foundations of social order.” New York: Routledge.

Wainer, J., & Braga, D. 2001. “Symgroup: applying social agents in a group interaction system.” Proc. 2001 International ACM SIGGROUP Conference on Supporting Group Work, 224–231.

Weber, S. 2004. The Success of Open Source. Harvard University Press.

Wiggins, A. and Crowston, K. 2010. “Reclassifying success and tragedy in FLOSS projects.” Proc. OSS.

Woolley, A.W., Chabris, C.F., Pentland, A., Hashmi, N., and Malone, T.W. 2010. “Evidence for a collective intelligence factor in the performance of human groups.” Science 330, 686-8.

Yamauchi, Y., Yokozawa, M., Shinohara, T., and Ishida, T. 2000. “Collaboration with lean media: how open-source software succeeds.” Proc. CSCW, ACM: 329-338.

Zoeller, N, Morgan, J. and Schroeder, T. 2019. “A Topology of Groups: What GitHub Can Tell Us about Online Collaboration.”

Appendix A

A.1 Data Distributions

The following figures show the data distribution for evaluation and potency data sets with two network structures, Network E and Network H, as outlined in Chapter 3.

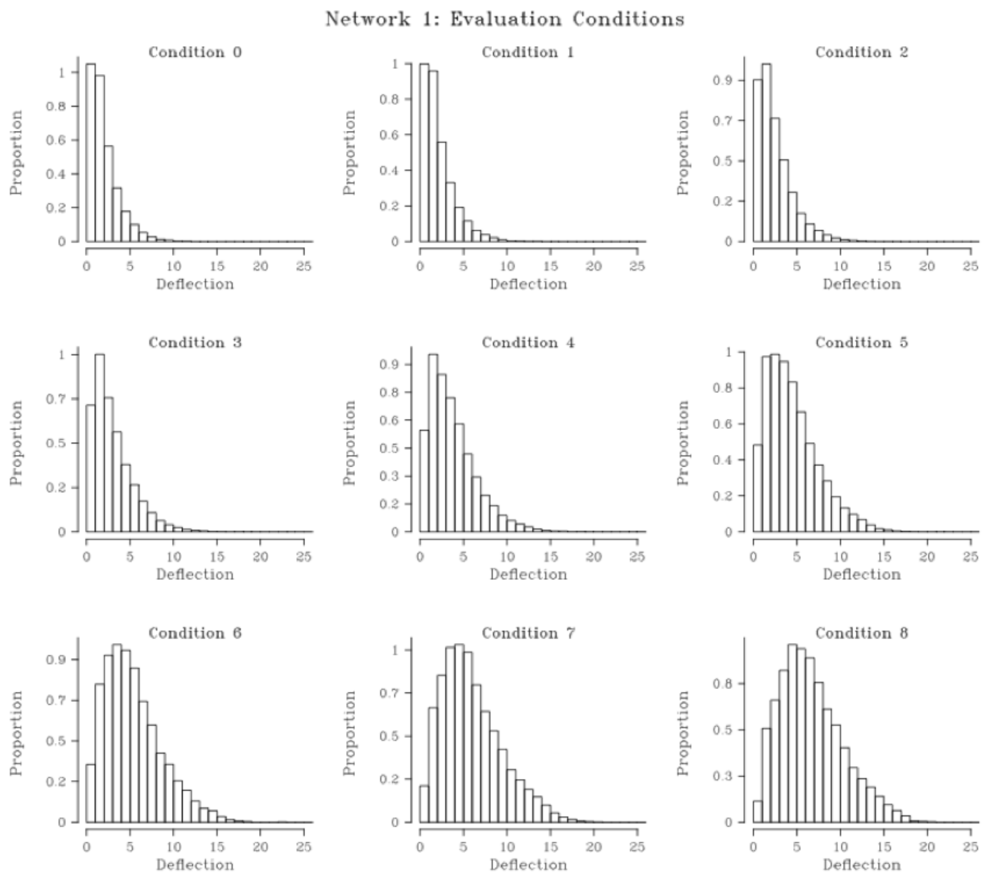


Figure A.1.1. Deflection Distribution for the Network E of the Evaluation Condition, showing the long-tailed distribution of the data

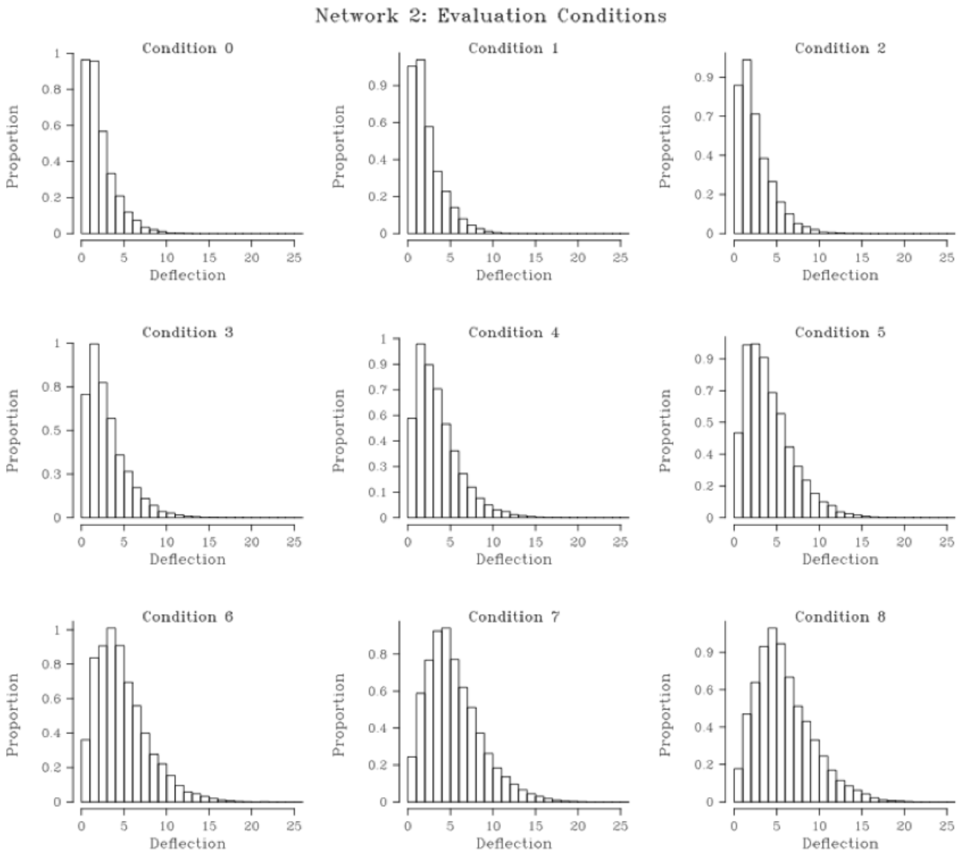


Figure A.1.2. Deflection Distribution for the Network H of the Evaluation Condition, showing the long-tailed distribution of the data

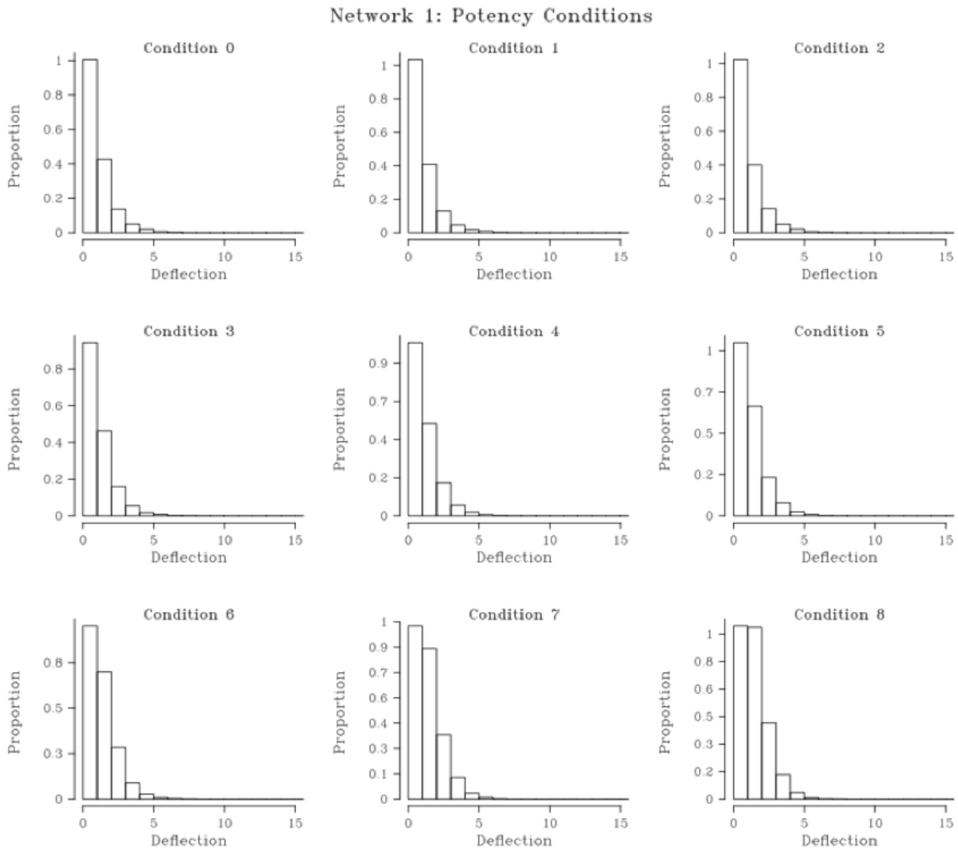


Figure A.1.3. Deflection Distribution for the Network E of the Potency Condition, showing the long-tailed distribution of the data

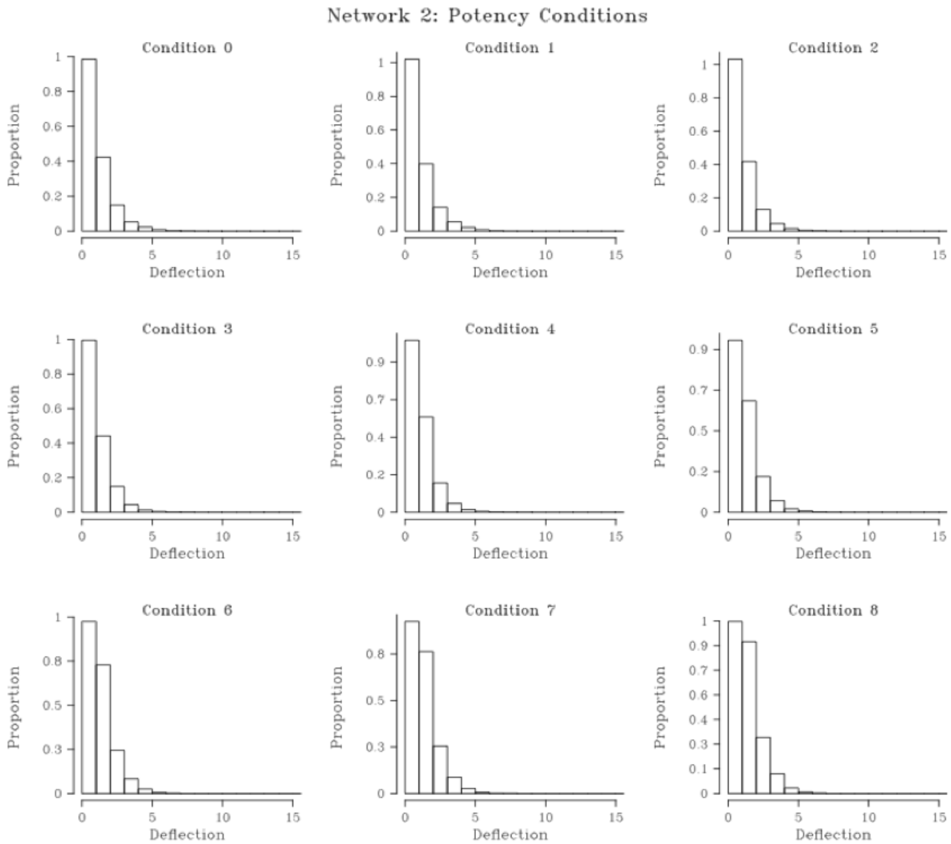


Figure A.1.4. Deflection Distribution for the Network H of the Potency Condition, showing the long-tailed distribution of the data

Figures A.1.1.-A.1.4. show the skewed distribution of my data, suggesting that the residuals around the mean are unlikely to be normally distributed.

A.2 Kruskal Wallis Tests

The Kruskal Wallis test is an analysis for variance. This rank-based nonparametric test can be used to determine if there are statistically significant differences between two or more groups of an independent variable on a continuous or ordinal dependent variable. I performed the Kruskal Wallis test to see if there were group-level differences in variation.

```
        rank-based (Kruskal-Wallis) Modified robust Brown-Forsythe Levene-type test based on the absolute
        deviations from the median with modified structural zero removal method and correction factor

data:  evaluation_networks[[1]]$Deflection
Test Statistic = 1762132, p-value < 2.2e-16
```

Table A.2.1. Kruskal Wallis Test for Network E of the Evaluation Condition

```
        rank-based (Kruskal-Wallis) Modified robust Brown-Forsythe Levene-type test based on the absolute
        deviations from the median with modified structural zero removal method and correction factor

data:  evaluation_networks[[2]]$Deflection
Test Statistic = 1126590, p-value < 2.2e-16
```

Table A.2.2. Kruskal Wallis Test for Network H of the Evaluation Condition

```
        rank-based (Kruskal-Wallis) Modified robust Brown-Forsythe Levene-type test based on the absolute
        deviations from the median with modified structural zero removal method and correction factor

data:  potency_networks[[1]]$Deflection
Test Statistic = 205518, p-value < 2.2e-16
```

Table A.2.3. Kruskal Wallis Test for Network E of the Potency Condition

```
        rank-based (Kruskal-Wallis) Modified robust Brown-Forsythe Levene-type test based on the absolute
        deviations from the median with modified structural zero removal method and correction factor

data:  potency_networks[[2]]$Deflection
Test Statistic = 130008, p-value < 2.2e-16
```

Table A.2.4. Kruskal Wallis Test for Network H of the Evaluation Condition

As Tables A.2.1-A.2.4. show, I found significant support for the alternative hypothesis: the groups' variation is heterogenous.

A.3 Van der Waerden Tests

I performed the Van der Waerden test, a non-parametric alternative to ANOVA, with a Bonferroni Correction.

```
        Pairwise comparisons using van der Waerden normal scores test for
              multiple comparisons of independent samples

data:  evaluation_networks[[1]]$Deflection and evaluation_networks[[1]]$Group_Type

  0      1      2      3      4      5      6      7     
1 <2e-16 -      -      -      -      -      -      -     
2 <2e-16 <2e-16 -      -      -      -      -      -     
3 <2e-16 <2e-16 <2e-16 -      -      -      -      -     
4 <2e-16 <2e-16 <2e-16 <2e-16 -      -      -      -     
5 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -      -      -     
6 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -      -     
7 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -     
8 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16

P value adjustment method: bonferroni
```

Table A.3.1. Van der Waerden Wallis Test for Network E of the Evaluation Condition

```
        Pairwise comparisons using van der Waerden normal scores test for
               multiple comparisons of independent samples

data:  evaluation_networks[[2]]$Deflection and evaluation_networks[[2]]$Group_Type

  0      1      2      3      4      5      6      7
1 <2e-16 -      -      -      -      -      -      -
2 <2e-16 <2e-16 -      -      -      -      -      -
3 <2e-16 <2e-16 <2e-16 -      -      -      -      -
4 <2e-16 <2e-16 <2e-16 <2e-16 -      -      -      -
5 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -      -      -
6 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -      -
7 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -
8 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16

P value adjustment method: bonferroni
```

Table A.3.2. Van der Waerden Wallis Test for Network H of the Evaluation Condition

```
        Pairwise comparisons using van der Waerden normal scores test for
               multiple comparisons of independent samples

data:  potency_networks[[1]]$Deflection and potency_networks[[1]]$Group_Type

  0      1      2      3      4      5      6      7
1 <2e-16 -      -      -      -      -      -      -
2 <2e-16 <2e-16 -      -      -      -      -      -
3 <2e-16 <2e-16 <2e-16 -      -      -      -      -
4 <2e-16 <2e-16 <2e-16 <2e-16 -      -      -      -
5 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -      -      -
6 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -      -
7 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -
8 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16

P value adjustment method: bonferroni
```

Table A.3.3. Van der Waerden Wallis Test for Network E of the Potency Condition

```
	Pairwise comparisons using van der Waerden normal scores test for
	       multiple comparisons of independent samples

data:  potency_networks[[2]]$Deflection and potency_networks[[2]]$Group_Type

  0      1      2      3      4      5      6      7
1 <2e-16 -      -      -      -      -      -      -
2 <2e-16 <2e-16 -      -      -      -      -      -
3 <2e-16 <2e-16 <2e-16 -      -      -      -      -
4 <2e-16 <2e-16 <2e-16 <2e-16 -      -      -      -
5 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -      -      -
6 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -      -
7 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 -
8 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16 <2e-16

P value adjustment method: bonferroni
```

Table A.3.4. Van der Waerden Wallis Test for Network H of the Potency Condition

Figures A.3.1-A.3.4. show the statistical significance of my data and lacking variation in significance, with all p-values less than 0.05, at 2.0×10^{-16}.

Appendix B

B.1 The Impact of Address to Group Rate on Affective Misalignment

The address to group rate sets the probability that actors direct their actions to the group as a whole rather than to specific agents. Figures B.1.1 (evaluation) and B.1.2. (potency) show the impact of the address to group rate (x-axis) on the median deflection experienced by the group (y-axis) as a function of increasing distance between Agent 1 and Agents 2 and 3 within egalitarian and hierarchical network structures. By increasing the value of evaluation or potency for one agent, Agent 1, and decreasing the value for Agent 2 and Agent 3, a hierarchy of cultural sentiment is created for the agents in the simulation. Agent 1 becomes increasingly good or powerful while Agents 2 and 3 become increasingly bad or weak. These simulations show a group's level of affective misalignment (deflection) is impacted by the interaction between network structure and distance between group members' identity sentiments. The identity values in Table 4.1 show how the sentiment differences plotted in Figure B.1.1, zero through eight, relate to the EPA values applied for Agent 1 vs. Agents 2 and 3.

E Distance	**Agent 1: E**	**Agents 2&3: E**	**P**	**A**	**Address to Group**
0	0	0	1	1	*varying*
2	1	-1	1	1	*varying*
4	2	-2	1	1	*varying*
6	3	-3	1	1	*varying*
8	4	-4	1	1	*varying*

Table B.1.1. EPA values selected to represent the full gradient of evaluation distance while varying the rate of address to group. Figure B.1.1 displays simulations run with agents with the identities in this table.

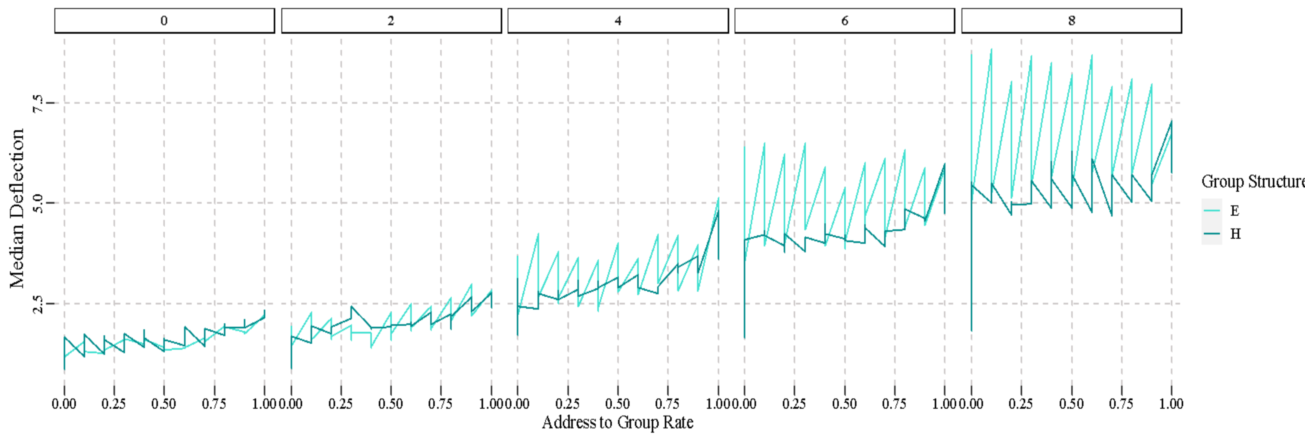


Figure B.1.1. Median deflection over evaluation distance of 0 to 8 in two group structures, egalitarian (light cyan) and hierarchical (dark cyan). The x-axis shows the deciles of address to group rates, from 0 to 100%, for each level of agent identity evaluation distance defined in Table B.1.1.

Figure B.1.1 shows the impact of the address to group rate on the median deflection a group is predicted to experience. Median deflection increases as the address to group rate increases in both egalitarian and hierarchical group structures and within each level of evaluation distance in agents' identities. Median deflection also increases as the evaluation distance increases from values of 2 to 7.7. The two colors of cyan, representing different network structures, reveal differences in deflection variation for each structure. For lower evaluation distance, the predicted deflection experienced by each group follows a similar range, but as the distance increases, egalitarian groups are predicted to experience more deflection. For hierarchical groups (dark cyan), the trend of increasing affective misalignment from the starting intercept at an address to group rate of 0 to the final intercept at an address to group rate of 1.0 is more apparent as the lines zig zag less. The lines in Figure B.1.1 appear as zig zags as the median deflection values encompass the deflection experienced by all three agents.

Figure B.1.1 also indicates that as the proportion of actions addressed to the group as a whole versus individual members increases, the interactions increasingly violate group members' expectations instead of confirming them. When one member of the group becomes increasingly good while the other two members become increasingly bad, interactions also increasingly violate group members' expectations. These two trends existed for both the network structure where all members could interact equally (E), and for the network structure where one member is in a position of structural power (H) but the members of the group in which all members can interact equally experienced more of a violation to their expectations and the values fluctuated more between members of the group.

The next simulation further shows how a group's level of affective misalignment is impacted by the interaction between network structure and distance between group members' identity sentiments, but by focusing on a potency distance between members. The identity values in Table B.1.2 show how the sentiment differences plotted in Figure B.1.2, zero through eight, relate to the EPA values applied for Agent 1 vs. Agents 2 and 3.

P Distance	E	Agent 1: P	Agents 2&3: P	A	Address to Group
0	1	0	0	1	*varying*
2	1	1	-1	1	*varying*
4	1	2	-2	1	*varying*
6	1	3	-3	1	*varying*
8	1	4	-4	1	*varying*

Table B.1.2 EPA values selected to represent the full gradient of potency distance in quintiles while varying the rate of address to group in deciles.

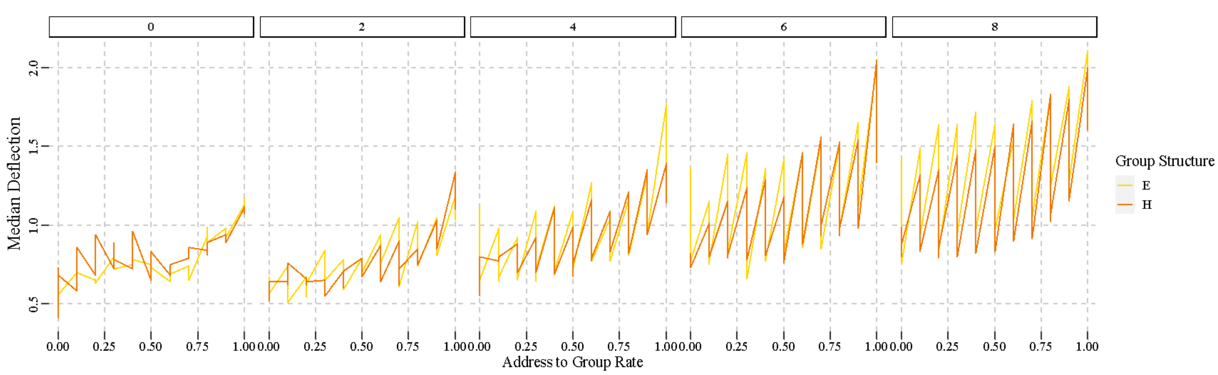


Figure B.1.2 Median deflection over potency distance of 0 to 8 in two group structures, egalitarian (light orange) and hierarchical (dark orange). The x-axis shows the address to group rates, from 0 to 100% increasing in increments of 0.1, for each level of agent identity potency distance, as defined in Table B.1.2.

The identity values in Table B.1.2 show how the sentiment differences plotted in Figure B.1.2 relate to the EPA values applied for Agent 1 vs. Agents 2 and 3. The address to group rate follows a similar trend of impact for the potency gradient as described above for evaluation. Median deflection increases steadily as the potency distance between agents increases, but the magnitude of increase is only from the values of 0.5 to 2.0. In Figure B.1.2, the egalitarian and hierarchical network structures fluctuate similarly, though the egalitarian group appears to experience slightly greater peaks of affective misalignment. As in Figure B.1.1, the zig zagging lines of median deflection in Figure B.1.2 represent the differences in deflection experienced by the three agents in the simulation.

As the proportion of actions addressed to the group as a whole versus individual members increases, the interactions increasingly violate group members' expectations instead of confirming them. When one member of the group becomes increasingly powerful while the other two members become increasingly weak, interactions also increasingly violate group members' expectations. These two trends were predicted for both the network structure where all members could interact equally and for the network structure where one member is in a position of structural power. Network structure did not greatly impact the predicted experience of each member in the group.

Two trends were common to both Figure B.1.1 and Figure B.1.2. First, as the proportion of actions addressed to the group as a whole versus individual members increases, the interactions increasingly violate group members' expectations instead of confirming them. Second, as the distance in goodness or power increases between one member of the group and the other two members, interactions also increasingly violate members' expectations. Though more apparent for evaluation distance, the network structure in which all agents interact equally produces increased violations of expectations and more variation in the experience of members of the group. These findings predict that groups with similar identities experience interactions that confirm their expectations more than groups with differing identities. Groups in which the proportion of actions addressed to the group as a whole are more limited experience interactions with less affective misalignment. These findings show the importance of similarities in respect and esteem or authority and control among members of a group and suggest that when differences in respect or esteem exist, a hierarchical network structure limits the violation of expectations experienced by members of the group compared to the experience in an egalitarian network structure.

B.2 The Impact on Affective Alignment of Boundary Conditions of Evaluation and Potency Distances

The evaluation and potency gradients examined so far have ranged from -4 to +4, centered around the value of 0. To observe the significance of a 0 threshold, which reflects a perceptual shift in viewing a given agent as fundamentally good or bad, powerful or powerless, Figure B.2.1and Figure B.2.2 examine differences in evaluation and potency from 0 to +2, centered around the value of +1. The differences were observed at increments of 0.2. Table B.2.1 shows the negative and positive evaluation gradients used to observe the 0 threshold in Figure B.2.1.

	Negative Gradient		**Positive Gradient**				
E Distance	**Agent 1: E**	**Agents 2&3: E**	**Agent 1: E**	**Agents 2&3: E**	**P**	**A**	**Address to Group**
0	0	0	1.0	1.0	1	1	0.4
0.2	0.1	-0.1	1.1	0.9	1	1	0.4
0.4	0.2	-0.2	1.2	0.8	1	1	0.4
0.6	0.3	-0.3	1.3	0.7	1	1	0.4
0.8	0.4	-0.4	1.4	0.6	1	1	0.4
1.0	0.5	-0.5	1.5	0.5	1	1	0.4
1.2	0.6	-0.6	1.6	0.4	1	1	0.4
1.4	0.7	-0.7	1.7	0.3	1	1	0.4
1.6	0.8	-0.8	1.8	0.2	1	1	0.4
1.8	0.9	-0.9	1.9	0.1	1	1	0.4
2.0	1.0	-1.0	2.0	0	1	1	0.4

Table B.2.1. Identity values selected to represent positive and negative gradients of evaluation distance in increments of 0.2 (+0.1 to Agent 1 and -0.1 to Agents 2 and 3 for each step) while holding the address to group rate constant at 0.4.

Figure B.2.1 uses the identity values defined in Table B.2.1 to compare the negative and positive evaluation gradients.

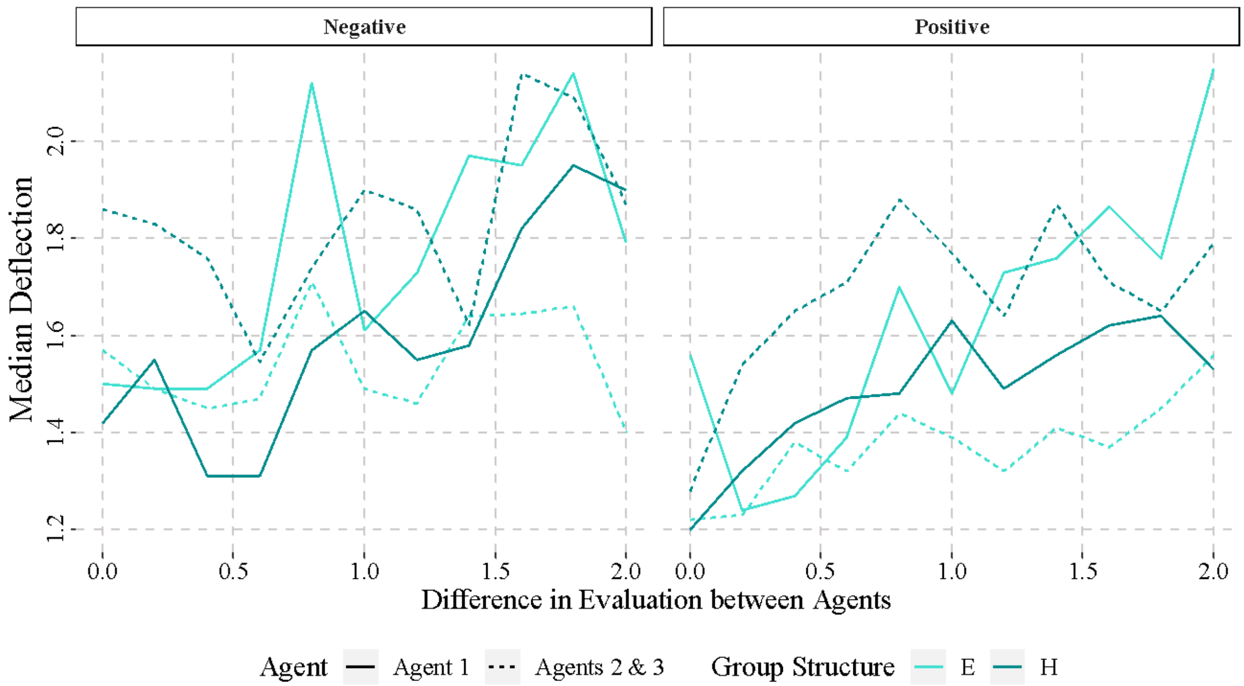


Figure B.2.1 Median Deflection comparing negative evaluation gradient, from E = -1 to E = 1, with positive evaluation gradient, from E = 0 to E = 2, to show importance of 0 threshold. Colors are used to represent group structure and agents are differentiated by Agent 1 (solid line) and Agents 2 and 3 (dashed line)

The fluctuation shown in Figure B.2.1 is due to the smaller increments run for these simulations (evaluation distance of 0.2 compared to evaluation distance of 1). In both gradients, the median deflection for Agent 1 and Agents 2 and 3 fluctuate and network structure does not greatly impact the median deflection experienced. Figure B.2.1 shows that in the two groups with equal, low evaluation distance, one group including negative evaluation values and the other including only positive evaluation values, group members experience similar violation and confirmation of their expectations.

Figure B.2.1 suggests that the perceptual shift in viewing a given group member as fundamentally good or bad does not greatly impact the affective misalignment experienced in the group. Perhaps, believing a group member is fundamentally good or bad does not change the amount of violation or confirmation of expectations experienced as expectations shift with perception. Even if the expectations differ in each group based on ones' perceptions, the expectations are still being violated and confirmed to similar extents.

Table B.2.2 defines the identity values used to observe the negative and positive potency gradients, used in Figure B.2.2 to analyze affective misalignment.

		Negative Gradient		Positive Gradient			
P Distance	**E**	**Agent 1: P**	**Agents 2&3: P**	**Agent 1: P**	**Agents 2&3: P**	**A**	**Address to Group**
0	1	0	0	1.0	1.0	1	0.4
0.2	1	0.1	-0.1	1.1	0.9	1	0.4
0.4	1	0.2	-0.2	1.2	0.8	1	0.4
0.6	1	0.3	-0.3	1.3	0.7	1	0.4
0.8	1	0.4	-0.4	1.4	0.6	1	0.4
1.0	1	0.5	-0.5	1.5	0.5	1	0.4
1.2	1	0.6	-0.6	1.6	0.4	1	0.4
1.4	1	0.7	-0.7	1.7	0.3	1	0.4
1.6	1	0.8	-0.8	1.8	0.2	1	0.4
1.8	1	0.9	-0.9	1.9	0.1	1	0.4
2.0	1	1.0	-1.0	2.0	0	1	0.4

Table B.2.2 Identity values selected to represent positive and negative gradients of potency distance in increments of 0.2 (+0.1 to Agent 1 and -0.1 to Agents 2 and 3 for each step) while holding the address to group rate constant at 0.4.

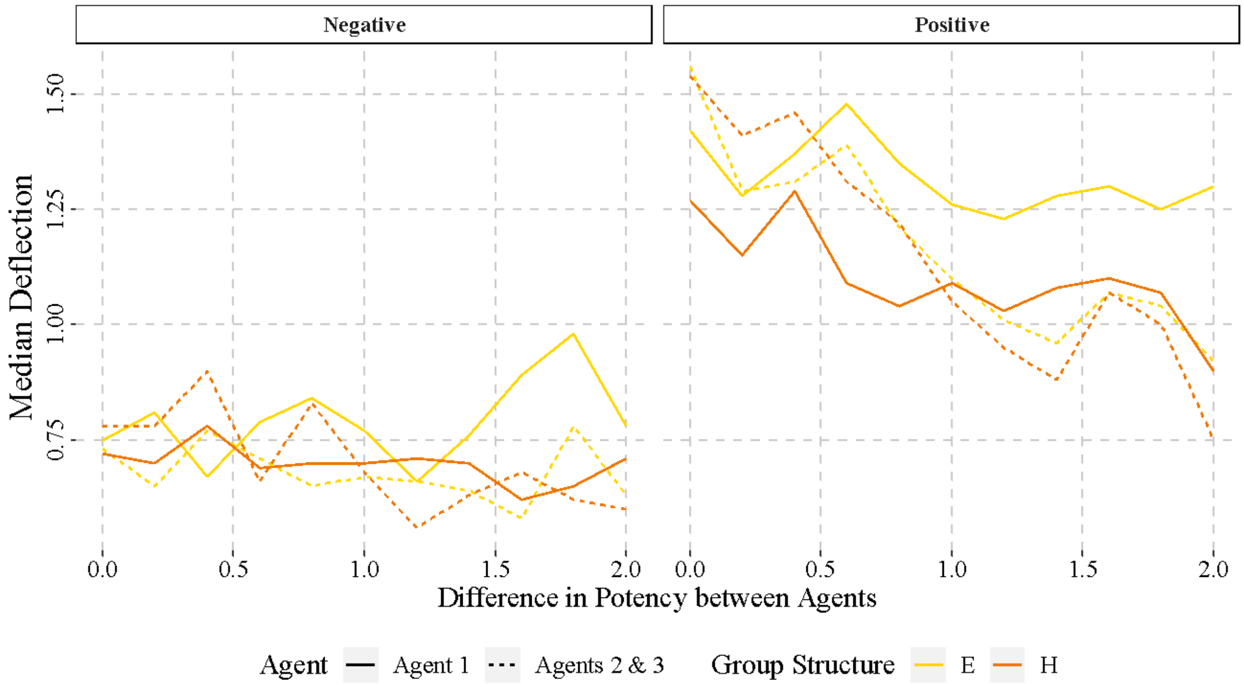


Figure B.2.2. Median Deflection comparing negative potency gradient, from P = -1 to P = 1, with positive evaluation gradient, from P = 0 to P = 2, to show importance of 0 threshold. Colors are used to represent group structure and agents are differentiated by Agent 1 (solid line) and Agents 2 and 3 (dashed line)

Figure B.2.2 shows that while low evaluation distance for both positive and negative gradients does not impact the amount of affective misalignment experienced in the group, low potency distance in each of the gradients produces differing amounts of affective misalignment experienced by the group. In both gradients, median deflection decreases as the potency distance increases, but the intercept of median deflection for the positive gradient at a potency distance of zero is slightly greater than for the negative gradient. It is important to note that the scale is quite small, only ranging from 0.5 to 1.5 for median deflection, so the changes shown in Figure B.2.2 are not very large, but the zero threshold appears to have a minimal impact on the predicted affective misalignment experienced by these groups.

Figure B.2.2 indicates that in groups of members with all positive potency identity values, the expectations of group members are violated most when the potency distance is zero. While previous findings show that agents who are acted upon by agents with equivalent potency will experience more deflection than agents acted upon by more potent identities (Morgan, Rogers, and Hu 2016), the deflection experienced might even be aggravated by the agents all having equivalent, positive potency identity values.