Between Implementation and Outcomes, Growth Matters:

Validating an Agent-Based Modeling Approach for Understanding

Collaboration Process Management

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Abstract

Increasingly, innovative collaborative partnerships are adopted in setting that distributed organizations, groups, and individuals work together toward solving problems or projects that are too big or complex for single investigators. We look at how the growth process, a largely overlooked aspect of collaboration affects stakeholders' expectation of each other's contribution to a civic program and subsequently influences collaboration outcomes. Based on experimental economics and complexity theory, strategic behaviors of stakeholders in collaborations are formalized as a minimum-effort coordination game with Pareto ranked equilibria. We implement the minimum-effort coordination game in a multi-agent simulation. A series of simulated experiments are conducted to gain a fine-grained understanding of how the growth process can engender and reinforce positive expectation among stakeholders, minimize uncertainty, and aid the coordination of stakeholders' behaviors in collaborative partnership. Additional experiments explore under what circumstances are the mechanisms more or less effective. Findings from this study not only help stakeholders in the collaborative partnership to understand and adopt appropriate growth mechanisms and achieve optimal outcomes; they also inform researchers and practitioner the important role agent-based modeling could play as a facilitative tool. The theoretical framework and the multi-agent method of this study help us to delve into the "black box" of collaborative processes and better explain the successful factors in policy implementation.

Keywords

agent-based modeling, collaboration, game theory, growth, implementation

Introduction

Collaborations, also known as Collaborative partnerships, are an innovative way for distributed organizations, groups, and individuals to work together as alliances among stakeholders and organizations from multiple sectors that work together toward a common goal. This strategy of working together is becoming increasingly common in civic engagement (Roussos and Fawcett, 2000: 369), business teams (LaFasto and Larson, 2001), academic fields (Cummings and Kiesler, 2005: 703), and almost all other settings. Federal and State health agencies routinely support, and often mandate, the formation of collaborative partnerships to design and implement non-profit community health initiatives (Hicks et al., 2008). The National Science Foundation (NSF) and other major funding agencies have emphasized the need for more distributed centers of research in order to solve problems of science and engineering that are too big for single investigators (Cummings and Kiesler, 2005: 703). Collaborative partnerships are also increasing in frequency within many other settings because of an increased complexity of problems, as noted by LaFasto and Larson (2001: xvii):

> A steady increase in collaborative teams was reported in the adoption of collaborative strategies in the auto, steel, and textile industries. A similar pattern was noted in science and technology. Collaborative problem solving processes are embraced by the health care industry, as well as by institutions and agencies that fund social programs and initiatives.

Malone (2004), in *The Future of Work,* explains this shift is work patters as the natural evolution toward the project as the central unit of interest instead of a specific institution. He asserts that projects traditionally handled by strict controlling hierarchies are now being taken on by collaborative partnerships, by which tasks are accomplished as if by "citizen participation" rather than by "hierarchically managed worker-bees." He further attributes the increase in collaborative partnerships to a change in the very nature of work, a change made possible because of the decreased cost of communication and increased availability of information, and an increased ability to process this information.

Previous studies of group coordination problems have provided considerable evidence to show the strong influence group size has on the group's collaborative outcome: as the size of the group increases, its ability to coordinate the actions of those individuals involved sharply decreases (Van Huyck et al., 1990: 234; Camerer and Knex, 2000: 194; Weber, 2006: 114). For example, for collaboration in academics, the number of institutions participating in the collaboration is inversely related to their success (Cummings and Kiesler, 2005: 703; Olson et al., 2005). A study of 62 NSF-sponsored projects found that, as the number of institutions involved in a collaboration increased, the level of success decreased (Cummings and Kiesler, 2005: 703). In a series of laboratory studies from 1990 to 2006, coordinating any group larger than 6 members within the lab was nearly impossible (Van Huyck et al., 1990: 234; Camerer and Knez, 2000: 194; Knez and Camerer, 1994: 101; Cachon and Camerer, 1996: 165; Chaudri et al., 2001; Weber, 2006: 114). The most current findings about how to achieve efficient coordination in large groups is provided by Weber's laboratory studies (2006: 114). He offers one possible situation in which people in large groups might coordinate effectively. For him, by starting the partnership with a small initial working group and then adding entrants slowly, the group can become large but still be coordinated efficiently. The initial stage of collaboration in which new members join existing collaborations that have already involved multiple organizations and individuals is called "the growth process". However, even using the growth process, successful collaboration is possible, but not likely. What remains unclear and might be more important for practitioners are when and how the growth process and those unidentified mechanisms could be effective as well as the comparison of the effectiveness of those mechanisms under certain circumstances. We look at how the growth process, a largely overlooked aspect of collaboration affects stakeholders' expectation of each other's contribution to a program and, subsequently, influences collaboration outcomes.

To understand the growth process in collaboration we employ the use of an agent-based model. The unique characteristics and the empirical strength of agent-based modeling make it an appropriate method by which to study the growth process collaboration. For example, in laboratory experiments, groups exist independent of context and larger social units (McGrath, 1991: 147). For studies in natural settings, it is difficult to experiment with various conditions, and avoid influencing the interaction of the groups while observing them. However, agent-based modeling can be used to understand the dynamic and process in certain contexts and might provide a more satisfying explanation of behavior observed in the environment (Lansing, 1991). Additional, the agent-based model, as an artifact form this study, could be a facilitative tool available during the decision making process. Furthermore, given such challenges associated with the usage of agent-based modeling such as the credibility and generalizability of results, we demonstrate how to develop a deliberate validation plan for the models.

The research program of this study includes three stages. First, based on experimental economics and complexity theory, strategic behaviors of stakeholders in collaborations are formalized as a minimum-effort coordination game with Pareto ranked equilibria. We implement the minimum-effort coordination game into a baseline model that is then calibrated with the previous twenty years of experimental findings of minimum-effort games (Van Huyck et al., 1990: 234; Camerer and Knez, 2000: 194; Knez and Camerer, 1994: 101; Cachon and Camerer, 1996: 165; Chaudri et al., 2001). Second, we expand the model to include the growth intervention and verified the model though a comparison with the latest findings from Weber's 2006 experiments. Finally, we run additional experiments explore under what circumstances are the mechanisms more or less effective.

Literature Review

Game Theory

Theories from economics and complex systems, specifically game theory, are borrowed to formalize the growth process of collaboration and its mechanisms. Game theory has a history of being used for theory construction and to provide insight into the dynamics of a system. In game theory, multiple players make individual decisions based on a pre-established payoff structure to achieve the best personal outcome. Game theory and repeated games provide a formal modeling approach for social situations where individuals interact with others. By now, repeated game play has been used to explore the emergence of complex group behavior by observing the interactions between individuals (Schelling, 1978; Holland, 1998), testing novel configurations in game theoretic experiments (Katz and Shapiro, 1985: 424; Ostrom, 2000:137), rationalizing the potential of organizational structures to self-organize in real world settings (Lansing, 1991; Holland, 1995), justifying new structures of information exchange (Axelrod, 2001), and exploring the development of common practices in policy development (Skryms, 1996). In this study, game theory is used so that the role of the growth process could be studied by naming the participants and available actions, formalizing the problem, and extending the rich experimental economics literature that studies coordination challenges in groups (Van Huyck et al., 1990: 234; Camerer and Knez, 2000: 194; Knez and Camerer, 1994; Cachon and Camerer, 1996: 165; Chaudri et al., 2001; Weber, 2006: 114).

Commonly used group games in the literature vary based on the type of coordination and the features of the game established by the payoff structure. There are three common notions for coordination. The first notion is from the "prisoner's dilemma" or "social goods" game in which individuals can either cooperate or defect; if we fail to coordinate, then someone benefits at someone else's expense (Axlerod, 1984). The second notion is pure coordination where if, in the case of a failure to coordinate, everyone loses; this is very different than someone gaining an advantage. For instance, failing to drive on the correct side of the street is in no one's best interest. There is a third notion of cooperation in which a group of people contribute diverse skills, abilities, and information to potentially achieve a super-additive outcome; we will do better than if we were all isolationists. Three games that test these aspects of coordination are commonly referred to as "social goods" games, pure coordination games, and minimum-effort games and are characterized by the dilemmas individual participants face when playing the game, the presence or absence of a risk-dominated strategy, and the presence or absence of an incentive to deviate, see Table 1.[1]

Game	Social Goods	Pure Coordination	Minimum Effort
Dilemma	Sacrifice Personal Wealth vs. Global Welfare	Align Strategies with Others	Personal Resource Security vs. Group Efficiency
Incentive to Deviate	Yes	No	No
Risk-Dominated Strategy	Yes	No	Yes
Example	Paying Taxes Leaving Feedback on EBay	Coin Flip Driving on the same side of the road	Chain-Building Game Stag-Hunt

Table 1 Comparison of Characteristics of Different Games

Social Goods Game:

Individuals facing the option to contribute personal resources (time, money, energy) toward a project that will benefit the group more than the direct return will benefit the individual characterize a social goods game, also called a public goods game (Katz and Shapiro, 1985, p. 424; Ostrom, 2000, p. 137).

Pure Coordination Game:

The basic form of a coordination game, usually called a pure coordination game, is characterized by complete symmetry between players, between strategies, and between equilibria (Mehta et al., 1994: 658). In this pure coordination game, players have the same payoff structure, the same strategies ("heads" or "tails") and the same expected value if either "heads" or "tails" becomes their unanimous choice. In the real world there is no benefit in being the only individual driving on the wrong side of the road.

Minimum-Effort Game:

The pure coordination game has been refined in several ways to represent more complex situations. One family of refined coordination games is referred to as minimum-effort games (Skryms, 1996 and 2004; Van Huyck et al., 1990: 234; Camerer and Knez, 2000: 194; Knez and Camerer, 1994: 101; Cachon and Camerer, 1996: 165; Chaudri et al., 2001; Weber, 2006: 114). In a minimum-effort game, players have to invest some effort to achieve a potential payoff, but the actual payoff to all players is tied to the effort of the person who contributes the least. Individuals playing the game are faced with the dilemma of protecting their personal resources or investing their resources toward a group goal that will improve the welfare of everyone involved, while facing the risk that others might not contribute and their investment will be lost. A simple example of a *chain-building* exercise can help clarify the nature and dilemmas inherent in the minimum-effort game. In the chain-building example a group of people have the task of building a linked chain that will be used to earn money for the group. Each person in the group is responsible for building one link of the chain. To do so, each person can choose to spend either $1 of their own money and build a weak link or $10 of their own money and build a strong link, see Figure 1.

$10 Strong Link

$1 Weak Link

Figure 1: Costs to Build a Strong or Weak Link

After each person has independently decided to build a strong or a weak link the links are joined into a chain and the strength of the chain is tested. The chain is only as strong as the weakest link, so that a chain is weak even if only one weak link is present; the exact number of weak links in the chain does not matter. Each member in the group will earn $5 if the chain is weak. If the chain is strong and made of entirely strong links, each member will earn $30. A person choosing to make a weak link will earn $4 regardless of the choices others make. A person choosing to make a strong link might either lose $5 or earn $20 depending on the links others choose to make. The chain-building example demonstrates the dilemma each individual of a group faces when deciding between personal resource security and group efficiency.

In this example of a minimum-effort game, when the players all coordinate to build the same type of link, the outcome is a game of *pure-strategy Nash equilibrium*. A "pure-strategy Nash equilibrium" exists when no player gains anything by being the only person to make a choice different than the rest of the group. When everyone makes the same type of link, the choice is sustainable as long as no new participants are added. The preference of outcomes between a strong-chain equilibrium and a weak-chain equilibrium are orderable because the game has different payoffs for different strength chains.

The *Pareto-optimal* outcome is for everyone to make the strongest links. A "Pareto-optimal" outcome is a combination of choices in which it would not be possible to improve the well being of one participant without making the other participants worse off. However, strategic uncertainty exists because a player is unsure of the strategies others may choose. As the number of players increases, the probability of someone building a weak link also increases. As the risk of someone creating a weak link increases, the probability increases that even people who would build a strong link in a lower risk environment might decide to build a weak link instead. With so many sources of risk and uncertainty about what others will choose, and thus which choice is the best choice, the only certain option is to build a weak link. Thus, as the uncertainty of others' actions increases, the difficulty of making a strong chain also increases.

Collaborative Partnerships as Minimum-Effort Games

To meet our research objectives, we must choose the game that best represents the nature of the collaboration, isolate the central conflicts and interaction challenges, and find the proper theoretical framework to examine the outcomes that develop from the interactions of individual participants. Then, we contextualize the growth process within this framework. Compared with more traditional teams, collaboration partnerships are unique in that when they are successful, the actions of individual actors come together in a decentralized yet coordinated action. In the collaboration, the participants normally have more choice over which projects to join (Roussos and Fawcett, 2000, p. 369; Johnston and Hicks, 2004, p. 136; Malone, 2004). In collaborative partnerships the dilemma similar to the chain-game occurs when individual participants choose between using their resources to further the goals of the collaborative partnership or to protect their personal resources (Hicks and Larson, 2003). Thus, a major obstacle in creating an effective collaborative partnership is coordinating the action of all the participants toward the group goals.

As previously mentioned, when people are invited to participate in collaborative activities they must make a quick, often intuitive judgment as to the likelihood that they will be exploited, rejected, or isolated by the others (Tyler and Lind, 1992). Even though coordinating toward a common goal might provide significant advantages over pursuing self-oriented goals, a judgment that investing in group goals will lead to a relatively high likelihood of exploitation, rejection, or isolation will lead people to pursue self-oriented lower risk, lower reward goals (Tyler and Lind, 2001). Therefore, the minimum-effort game captures many of the characteristics that occur when stakeholders have a choice in how to coordinate their efforts in collaborative partnerships.

The Growth Process

Under experimental conditions, successful coordination in groups was never achieved when the group size was larger than six (Van Huyck et al., 1990: 234; Camerer and Knez, 2000: 194; Knez and Camerer, 1994: 101; Cachon and Camerer, 1996: 165; Chaudri et al., 2001). However, laboratory studies by Weber showed that, at least for the minimum-effort game, the growth process was a unique intervention that could be used to increase the likelihood of effective coordination in large groups. In his experiments, 12 people played a minimum-effort game similar to those previously described with seven different chain strengths. The experiment was designed to test steady growth and whether new entrants observing the previous performance of the smaller group could produce groups coordinated to stronger-chain equilibriums than control groups that started out large and did not change size. The two conditions of the experiment were:

1. ***Control group:*** Twelve subjects played the game for twelve rounds;
2. ***Growth group***: New entrants observe the group's history of previous choices.

In each round each player chose a number 1-7 to correspond to the strength of chain link they wanted to build and gave their choice to the experimenter. The experimenter calculated the strength of the chain based on the minimum value given and then wrote the chain strength on a board for the group to observe. Before the next round the board was erased and the next round started. In the growth condition, at commonly known times, other participants joined the group of those actively playing in the game. The growth conditions ran for 22 rounds, compared to the 12 in the control group. Extra rounds were added so that in the growth condition the first two participants could repeatedly play the game before new participants joined. When playing in a group of two, repeated interactions increased, but did not guarantee the likelihood that the two would coordinate to a highly efficient equilibrium. In the history condition both people actively playing and those that were added later were present in the room. In both conditions all twelve people played in the last few rounds.

Results from this experiment shows that, the growth process was a potential intervention for achieving coordination in large groups with real people, something that had previously not been obtainable in a laboratory setting (Weber, 2006: 114). However, the growth intervention enabled, but did not guarantee, the strong-chain outcome of groups. Furthermore, Weber also found that the way in which the growth process was managed was also important for the success of groups playing a minimum-effort game (Weber, 2006: 114). To a large extent, Weber's study establishes the status quo of what is known about how to utilize the growth process to deal with the challenge group size causes for minimum-effort collaborations. This is also the reason why it is used in this study to verify the model.

Agent-Based Modeling

The unique characteristics and the empirical strength of agent-based modeling make it an appropriate method by which to study the growth process in collaborative partnerships. Within the agent-based model, computer-simulated agents serve as experimental "subjects" whose behaviors are controlled by specific behavioral rules. Interactions among agents could induce social structures, group level behaviors, and differences in performance outcomes. For example, Individual choices could be formalized as strategic behaviors in a game-theoretic minimum-effort game (Skryms, 1996 and 2004; Van Huyck et al., 1990: 234; Camerer and Knez, 2000: 194; Knez and Camerer, 1994: 101; Cachon and Camerer, 1996: 165; Chaudri et al., 2001).

Understanding the growth process in natural groups is particularly difficult for many reasons. Much of the empirical foundation of group theory comes from studying a specific type of ad hoc group in a laboratory with no history and a very limited future. The membership of the group is normally assigned, and the experimenter controls the simple tasks they perform. Laboratory groups exist independent of context and are not embedded in any larger social units (McGrath, 1991: 147). However, when studying groups in their natural settings, it is difficult to experiment with various conditions, observe enough critical variations to draw conclusions about causality, and avoid influencing the interaction of the groups while observing them.

Agent-based modeling can be used to test separate hypotheses and generate explanations of complex group behavior. Understanding the dynamics, history, and relations between agents in an environment can complement field studies and may be a more satisfying explanation of behavior observed in the environment (Lansing and Kremer, 1993: 97). Compared with traditional social science paradigms, such as statistical estimating and differential equations, agent-based modeling has five unique characteristics. First, it takes a bottom-up approach. Rather than seeking a centralized control mechanism for orderly behaviors of a system, agent-based modeling explores whether decentralized interactions among autonomous actors can lead to system-level regularities (Holland, 1995 and 1998). Second, an agent-based framework assumes adaptive rather than fully rational behaviors of actors (Axelrod, 1997). Actors with limited information and foresight adopt strategies through interacting with others. Third, an agent-based model allows heterogeneity among actors, whereas traditional social scientists often suppress agent heterogeneity in order to make their models tractable (Epstein and Axtell, 1996). Fourth, agent-based modeling focuses on dynamic processes that produce or disrupt equilibria rather than the static nature of equilibria (Epstein and Axtell, 1996). Last, traditional statistical or multi-equation modeling assumes linear, deterministic or predictive relationships among parameters, whereas an agent-based framework explicitly takes account of nonlinear, nondeterministic, or recursive interactions among multiple levels of actors.

Another advantage of agent-based modeling is that the model does not try to explain everything about the phenomenon of interest - simplicity is its strength. The model also avoids attempting to replicate the real world exactly. A model can show that something that has previously been explained in a complex manner might in fact be the result of a simpler explanation (Axelrod, 2003: 21). Instead of looking for correlations between characteristics and outcomes, agent-based models allow for the investigation of an entire process. They can also be used to isolate competing hypothesis because of the ability to control completely the experimental environment difficult to obtain in natural settings (Lansing, 1991; Nan et al., 2005). Agent-based models gain strength as a research method when they are part of a larger research program, as here when combined with laboratory experiments (Arrow et al., 2000).

Research Design / Methods

Two distinct phases of research are included:

- **Phase 1**

  The baseline model is grounded as a minimum-effort game and then and calibrated on previous experimental findings.

- **Phase 2**

  The model is then expand to include the growth intervention and verified through a comparison to the latest findings from Weber's 2006 experiments.

Phase 1: The Baseline Model

There are three goals for phase one. First, we introduce a baseline agent-based model of agents playing a minimum-effort chain building game. Second, the model is grounded based on game theory. Third, given the existing literature from previous laboratory experiments of different size groups playing minimum-effort games, we calibrate the model at the parameter and process level.

Description[2]

The following description explains the baseline model created using NetLogo (Wilensky, 1999). In the model, agents will play multiple rounds of the chain building game with each other. In each round, an agent will independently choose to build either a strong or weak link. After each agent has chosen whether to build a strong or weak link, they will receive a payoff based upon their own choices and the collective actions others chose, see Table 2.

		Collective Choices of Other Players	
		All Strong Links	One or More Weak Links
Choice of Individual Player	Strong Link	*Strong-chain-payoff*	*Sucker-payoff*
	Weak Link	*Weak-chain-payoff*	*Weak-chain-payoff*

Table 2 Payoff Table of Minimum-Effort Chain Game

There are significant limitations to using agent-based models as a research tool. While such models may be closely controlled, results derived in artificial situations do not always extend well to more naturalistic settings. One common complaint is that simplifying the model significantly decreases the credibility and applicability of the resulting findings. Agent-based models also normally face greater challenges of validation than more mature methods of scientific research (Axelrod, 2003: 21). However, these challenges can be overcome by creating a deliberate plan for validation at the onset of the modeling project. Validation is neither a simple nor clearly defined topic (Johnston, 2005). To validate our agent-based model we employ three validation processes proposed by Carley (1996): grounding, calibrating, and verifying.

Model Grounding

Grounding establishes the reasonableness of the model, showing that simplifications made from the real world do not trivialize the model and that other researches have successfully made similar assumptions to capture the key elements of the theory. The grounding of the model could be largely addressed in the discussion of game theory and why, in particular, the minimum-effort coordination game most closely represents the collaborative partnerships.

Model Calibrating

Calibrating the model is an iterative process of modifying its variables to fit the real data that is available. It occurs at both the process and parameter levels. For the process calibration, the overall design of the experiment in the model, up to twelve people playing a repeated minimum-effort game, was motivated by the design of laboratory studies (Van Huyck et al., 1990: 234; Camerer and Knez, 2000: 194; Knez and Camerer, 1994: 101; Cachon and Camerer, 1996: 165; Chaudri et al., 2001; Weber, 2006: 114). For the validation at the parameter level, the design of the model requires setting environmental variables to specific values for the experiment. To test the best practices of interest, two environmental variables—*average-attitudes and participation-update*—need to be calibrated to settings that produce a set of expect results in the baseline model and to be left at that level for the remainder of the model development.

To calibrate reasonable values for those variables, the model was run 1000 times for each of the 16 different combinations of four different *average-attitudes* values [0.5, 0.75, 0.9, 0.95] and four different values of *participation-update* values [0.2, 0.5, 0.75, 0.9] over different group-sizes [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12] for a total of 176,000 runs. The results were then compared to findings taken from the last seventeen years of experimental research into coordination within different size groups in minimum-effort games.

Phase 1 Results: The Baseline Model

Model Calibration

As previously mentioned, a series of laboratory studies from 1990 to 2006 was used to calibrate our baseline model (Van Huyck et al., 1990, p. 234; Camerer and Knez, 2000, p. 194; Knez and Camerer, 1994, p. 101; Cachon and Camerer, 1996, p. 165; Chaudri et al., 2001; Weber, 2006, p. 114). These findings are summarized in Figure 2.

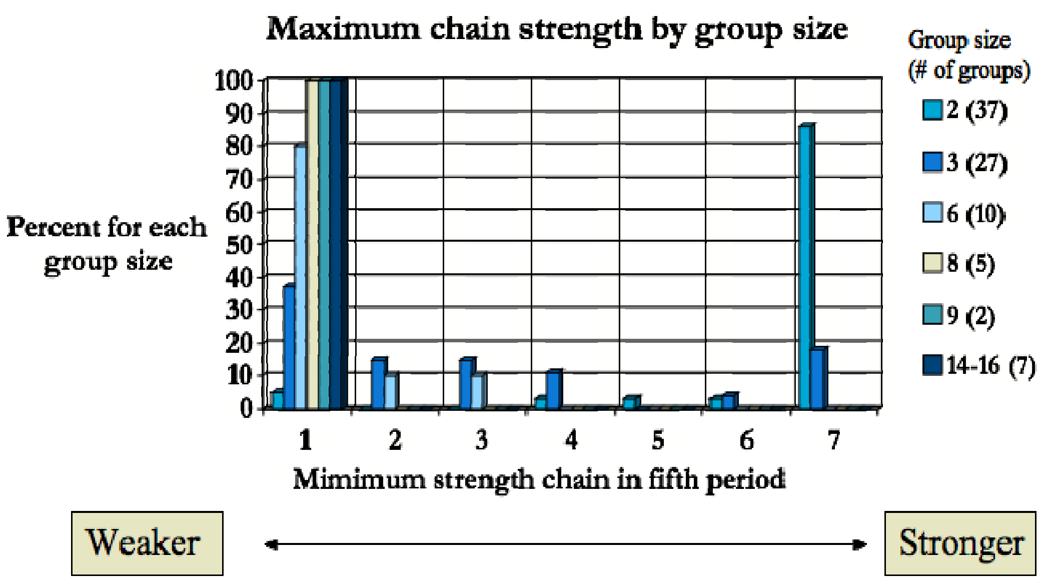

Figure 2 Maximum Strength Chain based on Group Size

In these studies the subjects participated in a 7-action minimum-effort game. To compare it with the chain-building example, the players build a chain by choosing between seven different strengths of chain links, and the payoff to the group is based on the weakest link. Also demonstrated in Figure 2, when a group is comprised of only two members, *eighty-six* percent of the time both participants coordinated to the strongest-chain equilibrium. Even the addition of one extra person drops the ability to coordinate in the strongest-chain equilibrium to *eighteen* percent. Six people were unable to coordinate any higher than the third worst outcome, and that was only *ten* percent of the time. Finally, groups of eight or more always coordinated on the *risk dominated equilibrium*, in which the participants choose to maximize their outcome regardless of what choices the others make. In this case the risk-dominated strategy is to build the weakest link.

In the laboratory studies, the minimum-effort game was played with seven different possible choices. To account for difference in the baseline model with only two choices, we perform the data transformation of treating any non-risk dominated outcome as a weak-chain outcome. To calibrate the model the results in the literature are compared with the results of the 16 possible configurations of variables on the basis of three criteria: value validation, point validation, and pattern validation (Carley, 1996).

- Percent of non-risk-dominated outcomes of two player games (value validation);
- Size above which participants could not coordinate and reach a non-risk dominated outcome (point validation);
- Same general pattern of results as size increases (pattern validation).

Based on these criteria, of the 16 possible configurations of variables, the best fit is produced by the setting in which the *average-attitudes* is 0.75, and the *participation-update* is 0.75, see Figure 3.

Applying the three criteria, we claim value validation because at group size 2, the 93.8% of model outcomes were not the risk-dominated outcome, and in the laboratory, across six studies and 37 groups of size 2, 95% of outcomes were not the risk-dominated outcome. We claim point validation, because in both the laboratory experiments and the model, some trials were able to coordinate to a non-risk-dominated outcome with a group-size of six, but not at group sizes larger than 6. And finally, we claim pattern validation because for a group size of 2, there was a high likelihood of coordinating to a non-risk-dominated outcome; however, the addition of even one extra person drastically reduces the ability to coordinate, and increasing group size additionally continued this pattern, both in the laboratory and in the agent-based model. A linear regression run on the model data found that the group size had a statistically significant relationship to the coordination outcomes ($p < .001$).

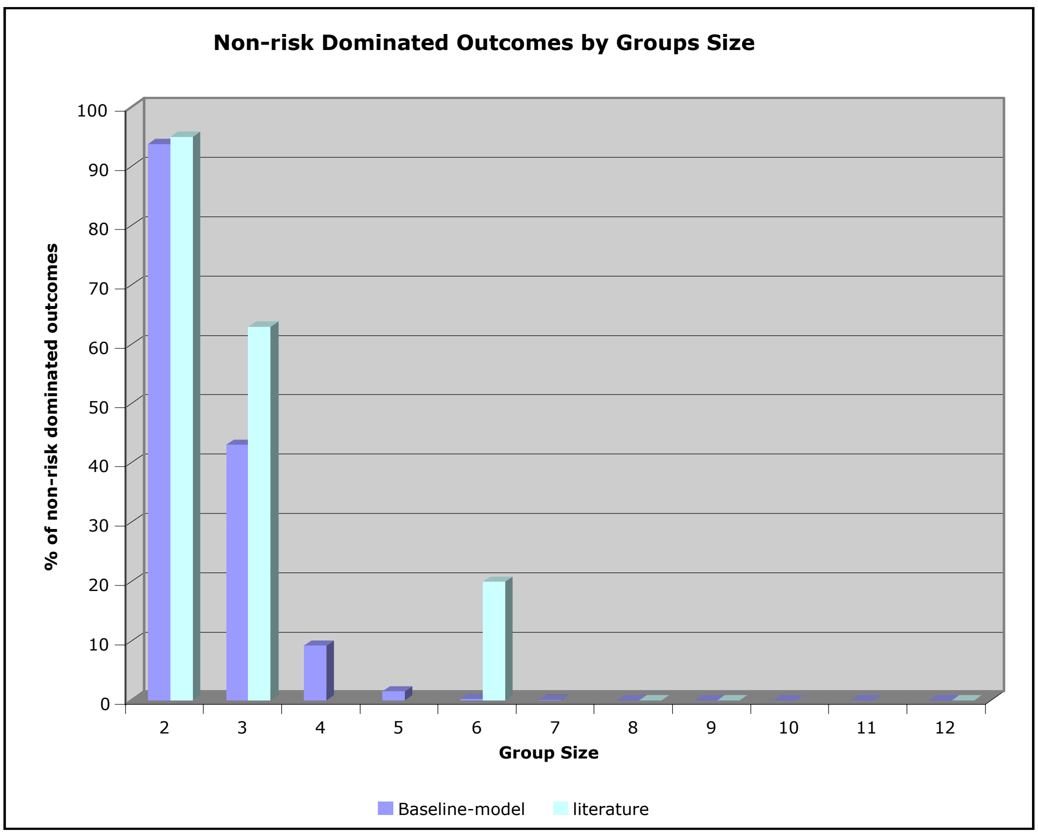

Figure 3 Comparison of Literature Results and Model Results with Best Fit Settings[3]

Phase 2: The Growth Model

Three steps are included in the second phase. First, the growth intervention is added to the baseline model to formulate the new growth model. Second, whether growth enables successful coordination in larger groups than a no-growth condition would be tested in the growth model. Finally, the growth model is verified with a laboratory finding that used a similar intervention (Weber, 2006: 114).

Growth Intervention[4]

The baseline model is extended to include the growth process and test whether using this intervention during the minimum-effort game will increase the likelihood of successful coordination in larger groups. In a run with a final *group-size* of 12, the game will start with two people playing the minimum-effort game while a third person watches. In the next round the person who was watching will join in the game play and a fourth person will be added to observe the game. This pattern continues until there are 12 players in the room all playing the game. Having a player observe one round before participating is motivated by an experiment that also uses growth in coordination games (Weber, 2006: 114).

Growth Model Verification

The growth intervention of the model is verified by comparing the results with the recent findings from a laboratory experiment that also used growth as an intervention to increase the likelihood of efficient coordination in large groups (Weber, 2006: 114). Results from that experiment have been partly discussed in the literature review part.

Phase 2 Results: The Growth Model

Effectiveness of Growth Process on Collaboration Outcome

Figure 4 shows the comparisons among results produced by the no-growth condition of the model, the no-growth laboratory findings from the literature, and the growth model. A one-way ANOVA comparison of the final outcomes of the growth and no-growth conditions for 11 different group-sizes (2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12) showed significant overall differences ($F(1, 4281) = 3.4$, $p < .001$.).

Therefore, in terms of improving the outcome of group collaboration, especially for large groups, the growth process matters.

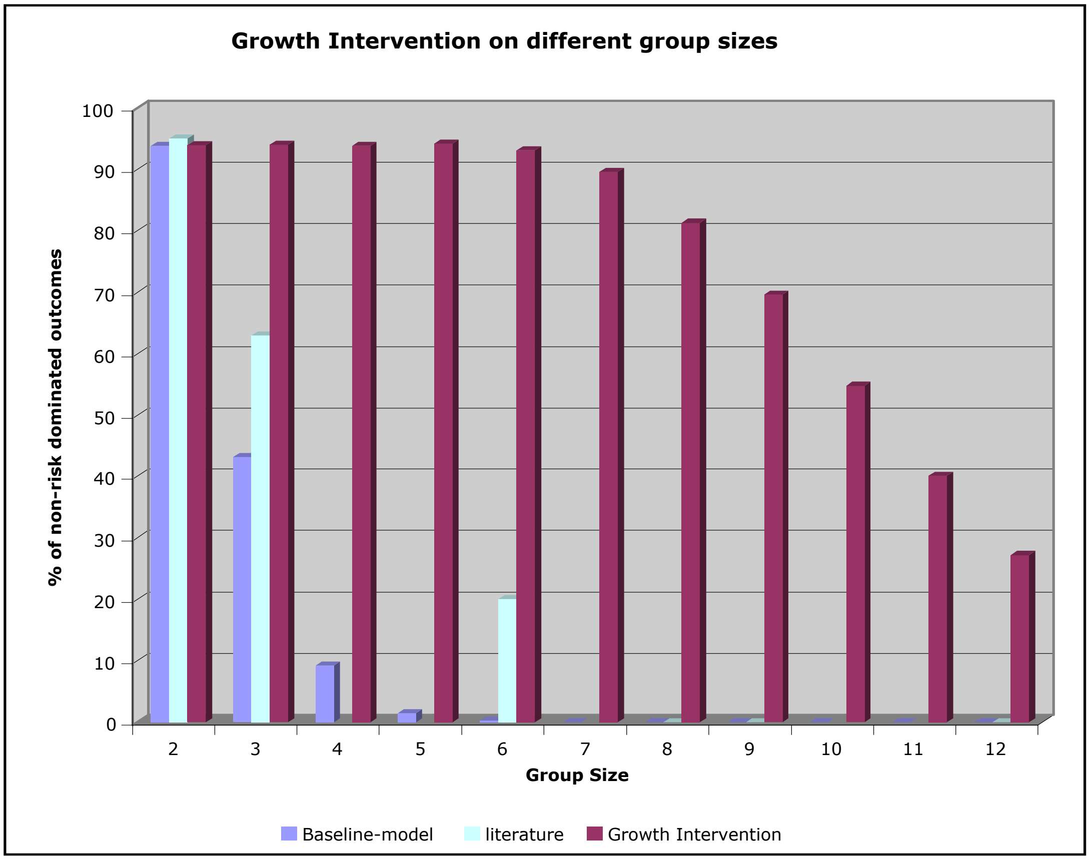

Figure 4 Percent of Non-Risk Dominated Outcomes with Different Group Sizes in Literature, Baseline Model, and Growth Model

Model Verification: Verification based on Experiment Results

Weber's Laboratory Results

In Weber's experiment, the control group with no growth that started out at a large size mimicked the results of previous experiments in which no groups were able to coordinate above the risk-dominated, weak-link strategy. In the history condition, when the group was of size two they were able to coordinate to a Pareto-efficient, strong-chain outcome. Groups that grew when new members observed previous behavior were able to coordinate at higher levels of efficiency, including the strong-chain outcome. However, growth did not guarantee the strong-chain outcome. In some cases these groups reverted to the risk-dominated strategy. Subjects in the growth condition were able to coordinate on the strong-chain outcome 22% of the time, on the risk-dominated, weak-chain outcome 44% of the time, and somewhere in between (medium strength chain) 33% of the time. If the initial stages of the game produced the risk-dominated outcome, then the end result was also a risk-dominated outcome. Every time that a strong chain was the final outcome, the initial interactions also resulted in a strong-chain outcome. This experiment shows that the use of growth is a potential mechanism for achieving coordination in large groups with real people, something that had previously not been obtainable in a laboratory setting.

Comparison of Laboratory with Model

In both the model and the laboratory experiment the growth intervention enabled, but did not guarantee, the strong-chain outcome of groups of size 12. A close examination of the model outcome also finds that the pattern of individual results follows the qualitative results of the Weber (2006: 114) experiment, as mentioned above. Both methods found groups that were not able to coordinate above the risk-dominated outcome in the first round, groups that coordinated for a few rounds and then transitioned to the risk-dominated outcome before reaching the full group size, and groups that coordinated the entire time. The general proportion of groups that were able to coordinate the entire time was also similar: 27% for the agent-based model and 22% for the laboratory experiment using the calibration settings from the baseline model. Finally, in either the lab or the model, there were no groups that started out within the risk-dominated outcome and then transitioned to the strong-chain outcome.

Discussion

A baseline agent-based model of agents playing a minimum-effort chain building game was introduced. The model was calibrated at the process level by mimicking the design of previous experiments that used the minimum-effort game. The variables of the baseline model were calibrated by comparing model outcomes of different size groups with different variable settings to a collection of laboratory experiments of different size groups playing the minimum-effort game. The model was then expanded to include a growth intervention with observation. Findings from the model showed that growth with observation was an effective mechanism to increase the likelihood of successful coordination within groups. Although there was an improvement in the overall performance outcomes, the largest groups were still only able to coordinate to the strong chain outcome only 27% of the time. Within the model, coordination failures occurred either because the initial participants failed to coordinate to a strong-chain outcome or a strongly performing group added a new member that disrupted the group's coordination, resulting in a weak-chain outcome. The growth model was then verified by comparing its pattern of results to the pattern of results produced in a recent laboratory experiment that used a similar intervention (Weber, 2006: 114).

In this study, we apply the agent-based modeling approach to resolve the challenging problem: how to achieve successful collaborations. By formalizing the collaborative partnership as minimum-effort game, we develop an agent-based model. The theoretical development, the agent-based modeling and findings in this study could contribute to both research and practice in the following ways. First, it provides more comprehensive and deeper understanding of the influence of the growth process on minimum-effort collaborative outcomes. Besides confirming previous findings in a new way, it demonstrates the agent-based modeling as a valuable tool to obtain knowledge. Furthermore, this study is also a pertinent example that shows how agent-based modeling could inform decision makers and help them make choices. Both the model and experiment results have important implications for the decision making process. Although the generalizability of findings produced is limited, it could still provide us important or new understandings that could not be obtained from other research tools. For this research, the model provides some unique and important guidance into interventions and practices that could help increase the likelihood that groups, especially large-size groups, will coordinate successfully.

Like all good models, the baseline and growth models provide some insights into the larger phenomenon of interest and also raise additional questions. Both the model and the laboratory study show that early interactions are very important. This is consistent with previous findings. Gersick (1988: 9) studied the entire life cycle of eight naturally occurring teams and found that people's first interactions with each other set lasting precedents that affect the ways in which members of the team will relate to each other and perform for the remainder of the project. In the model, groups that started as weak-chain builders were never able to switch and become strong chain builders. In the lab, groups that did not have early strong-chain interactions also never transitioned to strong-chain builders later in the experiment. By observing the model in progress, rather than simply recording the final outcome, it was apparent that in the growth cases that started out with early coordination but then failed, it was the addition of new participants and the choices they made that caused the group to fail.

Further Research

Until recently, the growth process and the challenges associated with when and how people join a collaborative partnership have been largely overlooked. In the majority of group research, as with Gersik's work, the established group has been the central unit of investigation (Kelly et al., 1990: 283; McGrath, 1991: 147; Wrochel, 1994: 147; Arrow et al., 2000). The challenge of transferring to program outcomes the benefits of including a growth process in the initial planning stage raises the question: what is it about the growth process that matters? The challenge of transferring to collaboration outcomes the benefits of including a growth process in the initial planning stage raises the question: does the management of growth process matter and how?

As previously mentioned, one of the biggest challenges for studies employing agent-based modeling as research instruments is the validation of the model. One important further development for this study is to collect relevant field data to verify those results produced by the model. Such a "testing-validation-testing-validation-……" cycle could lead to a valuable and adaptable tool with which researchers can design interventions for more successful collaborations in various groups as well as providing examples for the conditions where the findings hold.

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Notes:

1. A Prisoners dilemma game is a common form of two player social goods game.
2. For a detailed description of agents, the environment, and interaction rules, and measurements please see *Part 1: Baseline model details* of Appendix 1.
3. The laboratory experiments used for comparison did not test groups of sizes 4, 5, 7, 10, or 11.
4. For a detailed description of agents, the environment, and interaction rules, and measurements please see *Part 2: Growth model intervention details* of Appendix 1.

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Appendix

Part 1: Baseline model details

Agents

There are two types of agents in the model, players and links.

Players

Players are created with one attribute, their *generic attitude* toward other players (see Figure 5).

Figure 5: A typical player

This level is a value from 0 – 1. *Generic-attitude* * 100 represents the percent likelihood they think a player they have no other information about would build a strong link. The *generic-attitude* for each agent is randomly drawn from a normal distribution with a mean determined by the environmental variable *average-attitudes* and a standard deviation of .2. If the result of the random draw is greater than 1 or less than 0, then generic-attitude is set to 1 or 0 respectively for that player.

Previous findings justify the use of a *generic-attitude* variable to estimate others' behaviors. According to the economics literature on coordination games, the main issue in coordination results from a player's uncertainty over what others will do (Crawford, 1995, p. 103; Weber, 2005). The *generic-attitude* variable reflects this uncertainty.

Links

The second type of agent in the model, links, represents and maintains the attitude one player currently has toward another player. Each player maintains a relation to each of the other players in the model by individual directed links. The links are initialized based on the *generic-attitude* of the player from which they emanate. Figure 6 shows links emanating from player 0 toward both players 1 and 2. Not shown in the figure are the links that players one and two have toward each other and toward player 2.

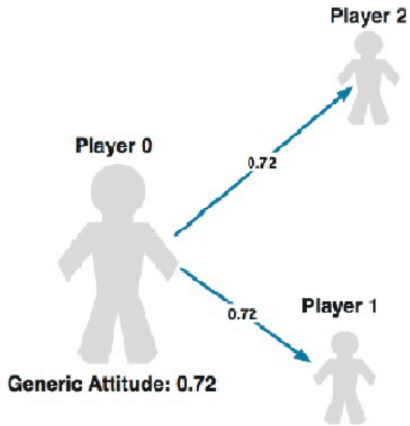

Figure 6: A player and the attitudes held toward other players stored in links

As the game is played, the attitude held in each link is updated.

Environment

The environment for the baseline model consists of six (environmental) variables: *group-size*, *average-attitudes*, *participation-update, strong-chain-payoff, weak-chain-payoff, and sucker-payoff*.

Group-size

The *group-size* variable is the independent variable in the baseline model experiment. *Group-size* is set between 2-12 to represent how many players are participating in the experiment.

Average-attitudes

The *average-attitudes* variable is the mean of the normal distribution that a player's *generic-attitude* is drawn from. The *average-attitudes* value can be set from 0 to 1. Higher levels of this value represent a population that, on average, will believe that other players are more likely to build strong chains. For the baseline model, this value was calibrated at 0.75.[1]

Participation-update

The *participation-update* variable is a model setting and it is applied to all links to calculate to what degree a player will change their attitudes of other players' next actions based on the outcome of the current round. This variable can be set from 0 to 1. A value of 0 represents that no change in attitude will be made. A value of 1 will change a links attitude to either 0 or 1 based on the outcome of round.

Payoffs

The payoffs for the minimum-effort game follow the form that the strong-chain payoff is higher than the weak-chain-payoff, which in turn is higher than the sucker payoff (Skryms, 2004). The specific values of each payoff were set according to the payoffs used in the minimum-effort game in agent-based model used in Johnston (2006), see Table 3.

		The collective choices of other players	
		All strong links	One or more weak links
Individual player's choice	Strong link	*Strong-chain-payoff (8)*	*Sucker-payoff (0)*
	Weak link	*Weak-chain-payoff (3)*	*Weak-chain-payoff (3)*

Table 3: Agent-based model payoff table

Interactions / rules

This section details how the model represents the experiment, from the setup through the steps of each round.

Setup

The model creates a group of agents equal to the group-size variable. For example, Figure 7 shows a sample initial set up an experiment with a *group-size* of 3 and *average-attitudes* 0.75.

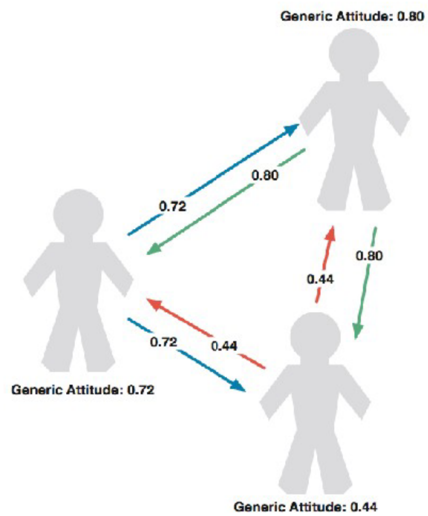

Figure 7: A generic setup of *group-size* 3

Each agent has a *generic-attitude* drawn from a normal distribution based on the *average-attitudes* variable. The player's individual attitudes toward other players are stored in the links emanating from them.

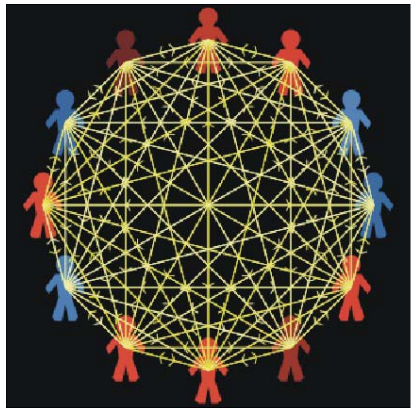

Figure 8: Screen-capture after setup with group-size 12

See Figure 8 for a screenshot of the setup of the baseline model with *group-size* 12.

Playing a round

A round consists of each player making a choice to build a strong or weak link, receiving a payoff based on their choices and the group outcome, and then updating their attitudes of the other players based upon the group outcome.

The first step of each round has every player choose to build a strong link or a weak link. To make this choice each player independently calculates the expected value of choosing to build a strong link based upon their current estimate of attitudes of the other players in the room. Specifically, they use the following calculation:

> *Expected value of a strong-link choice = my-attitude-toward-player 1 * my-attitude-toward-player 2 * … my-attitude-toward-player-n * strong-chain-payoff*

A player will choose a strategy based upon the highest expected value of all available strategies (Winter and Szulanski, 2001, p.730). If the calculated expected value of a strong-link choice is greater than the weak-chain-payoff, then the player will choose to build a strong link. If the calculated expected value of a strong-link payoff is less than the weak-chain-payoff, then the player will choose to build a weak link. There is no need to calculate an expected value for a weak-link choice because the payoff of choosing to build a weak link is always the weak-chain payoff, regardless of what others choose. In the model, agents who build a strong link are shown in blue, and those who build a weak link are shown in red, see Figure 9.

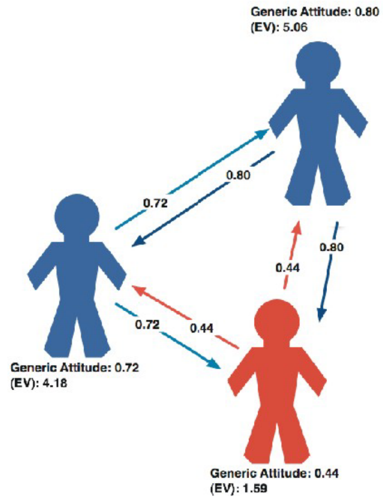

Figure 9: First round choices based on a comparison of the expected value of a strong link choice and the weak-chain payoff of three

The final step of each round is for each of the players to update their attitudes toward the other players based upon the group outcome. The group outcome is used to simulate the same information present in the laboratory experiments, wherein at the end of each round the experimenter would announce only the minimum choice of the participants without revealing players' individual choices.[2] If the group-outcome was a weak chain, each attitude would be updated using the *participation-update* variable according to the following calculation:

*updated-attitude = current-attitude – (current-attitude * participation-update)*

If the group-outcome was a strong chain, each attitude would be updated using the *participation-update* variable according to the following calculation:

*updated-attitude = current-attitude + ((1 – current-attitude) * participation-update)*

For example, if the three agents in the figure played one round, then two players would choose to build a strong link and one player would choose to build a weak link. The outcome would be a weak chain, due to the presences of one or more weak links; the weak link player would receive the weak-chain payoff, and the strong link players would both receive the sucker payoff. Afterward, they would update their attitudes using the first equation with a participation-update variable of 0.75. Figure 10 shows the updated attitudes, and the expected values and choices for round 2.

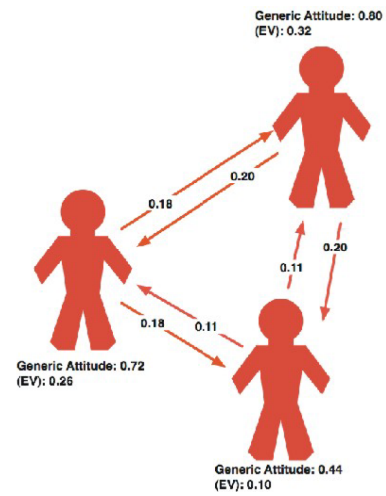

Figure 10: Round 2 choices, attitudes, and expected value for strong-link choice. All expected values are less than the weak-chain payoff of three, so all players choose to build a weak link (red players).

The model then runs another round in which the agents each make a choice, receive a payoff, and update their attitudes of other players. In the baseline model, each experiment is run for 12 rounds.

Measurements

The dependent variable in the baseline model is the group outcome of the final round of the experiment. The example shown in figures 5, 6, 7, 8, 9, and 10 would be a weak-chain outcome.

Part 2: Growth model intervention details

Agents

Both players and links have the same characteristics as players and links in the baseline model. Players agents are extended to have a binomial variable *active?*. If *active?* is set to true then a player is actively playing in a particular round. If *active?* is set to false then they are observing the outcome of the round, but they are not participating in the game or influencing the outcome of the game. Observing agents in the model are represented by the color gray.

Environment

The group-size variable represents the final size for the group. All groups start with only two active players and add one player each round until the final group size is reached. One new variable in the growth model is the *observation-update* variable. Similar to the *participation-update* variable, this variable is used to update the attitude, based on the round-outcome that an active player has toward a participant observing, but not participating in the game play. Knowing someone observed an outcome is a way of knowing that the two players have both observed the same events in the model's history, though it does not provide the same degree of information as actually having played with another person. For this reason, the observation-update variable is set between 0 – 1 and is less than the participation-update variable. In the model, the observation-update variable is set to 0.5.

Interactions / rules

The baseline model will be run adding one player to the game each round until the simulation reaches the final group-size.

Setup

In group-sizes of 3 or higher, during the setup of the model, three players and their associated links to other players are created. Two players have *active?* set to true and the third player has *active?* set to false, see Figure 11.

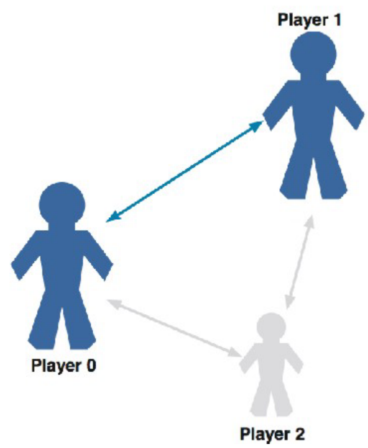

Figure 11: Setup in growth condition of group sizes 3-12. Blue players are active and making a strong-chain choice; the gray player is observing the play of the others

Play round

Playing a round is similar to the baseline model, where players make a strong or weak link choice, receive payoffs, and update their attitudes toward others. However, in the growth game, only players with *active?* set to true make a strong or weak link choice, and that choice is based on an evaluation of their attitudes toward only other players with *active?* set to true.

Updating attitudes

The final step of each round is to update the attitudes of players toward all other players, based upon the group outcome. Both active players and observers update their attitudes toward all other players based on the group outcome in each round. If the group-outcome was a weak chain, each attitude toward people who participated would be updated using the *participation-update* variable according to the following calculation:

*updated-attitude = current-attitude – (current-attitude * participation-update)*

If the outcome was a strong chain:

*updated-attitude = current-attitude + ((1 – current-attitude) * participation-update)*

If the group-outcome was a weak chain, the attitude of all links directed at people who observed would be updated using the *observation-update* variable according to the following calculation:

*updated-attitude = current-attitude – (current-attitude * observation-update)*

If a the outcome was a strong chain:

*updated-attitude = current-attitude + ((1 – current-attitude) * observation-update)*

At this point all existing attitudes have been updated based on the group outcome and activity status of the players.

Next round

At the beginning of the next round, and all rounds until the final round, the following sequence of events occurs. First, the player that observed in the previous round is made active and will participate in the current round. Next a new player is added to the room to observe, see Figure 12.

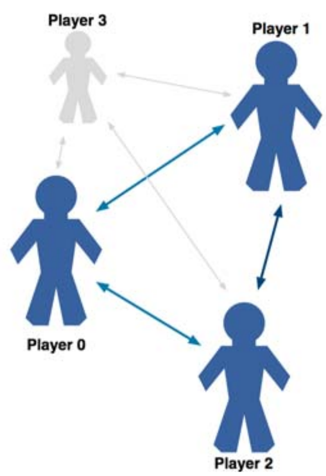

Figure 12: Growth round 2, now three active players and one new observer

When the new player is added to the room, new links are created from each current player to the new player based on each individual's *generic-attitude*. For the new player, they form links to all existing players based upon their own *generic-attitude*. The new player is not active and does not participate in the next round of the game.

Final round

In the final round of the growth model the new participant that was added in the previous round is made active, and no new participants are added. All players play one final round of the chain-building game.

Measurements

There are two possible outcomes of the model. Figure 13 shows a screen-shot from the Netlogo growth model of a weak-chain outcome, and Figure 14 shows a screen-shot of a strong-chain outcome.

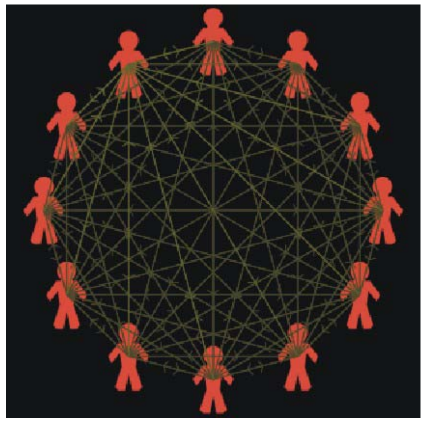

Figure 13: Weak-chain outcome

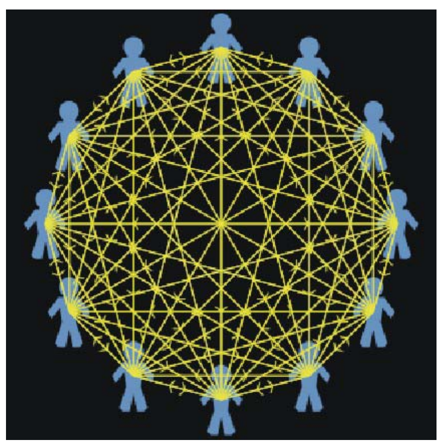

Figure 14: Strong-chain outcome

The brightness of the links represents the attitude of one player to another. Brighter links indicate an attitude that someone is more likely to build a strong link. A faded link indicates an attitude that someone is less likely to build a strong link. The brightness of the players also represents the certainty with which they made their choice to build a link. Faded players are close to the threshold between choices.

Notes to Appendix

1. Other values for *average-attitudes* tested were 0.50, 0.90, and 0.95. The use of a value of 0.75 is justified in the model calibration section.

2. While in small-size games it might be possible to deduce the specific actions of the other players, that dynamic was not replicated in the model.