Modeling relationship dynamics in GM's research-institution partnerships

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Abstract

GM has initiated partnerships with firms and research institutions at a rapid pace. One effort of the multi-disciplinary research team involved the construction of a relationship dynamics model to assist in partnership planning and management. Earlier research on private-sector partnerships indicated that partnership success is largely dependent upon the development and maintenance of strong, productive relationships between the partners. Therefore, modeling efforts focused on the relationship itself. To increase the likelihood that the resulting model is realistic, valid and representative, empirical data was combined with a systems-dynamics approach, and the model is being validated with feedback from study participants.

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1. Introduction

Many organizations and institutions today are engaged in a wide variety of partnerships. GM, for example, has been involved in partnering for over 30 years. Initially, these relationships involved alliance partners in which some form of equity relationship was common[1]. While this trend continues, other types of partnerships have been created including those with private-sector firms in which GM has no equity, and with a variety of US and non-US research institutions. Over time, the type and number of these partnerships has dramatically increased

Each of these partnership types is perceived to have numerous benefits. GM R&D relationships with research institutions are designed to enhance GM's competitiveness. R&D seeks to leverage partner knowledge and expertise. Partnering enables GM to tap into rapidly expanding technical fields and bring that knowledge to bear on corporate problems. One GM executive commented: "Innovation networks, such as this partnership, will function as incubators for new ideas. The fastest way to deliver innovation is to work together" (GM Press Release, 2001). For R&D's university partners, known as Collaborative Research Labs (CRLs), the partnerships afford opportunities for university faculty and students to learn about and contribute to "real-world" problem-solving. In exchange, they receive research funding for a specified number of years, and can often take advantage of internships and other work-related opportunities for both students and faculty.

Because of the significant investment of R&D time and resources into this increasingly popular business strategy, R&D management launched a major program to study these partnerships. Our multi-disciplinary research team developed a proposal, and subsequently began a multi-phase study to understand partnership functioning.

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Our goals were to investigate the structure and dynamics of these R&D partnerships, develop a model to diagnose and predict partnership difficulties, and identify ways of enhancing partnership effectiveness.

We know from past studies that strong, effective partnerships are rare because of the high rates of partnership failure – upwards of 60 percent with some as high as 80 percent (Duysters *et al.*, 1999; Ertel *et al.*, 2001; Gulati *et al.*, 1994; Spekman and Lamb, 1997). These failures are largely associated with the social and cultural differences between the partnering organizations. For example, partners may have different goals for the partnership, different ideas about how to achieve those goals, or different expectations for the time and resource commitment necessary to accomplish those goals. When there are significant differences in alignment between the partners, conflict typically results, leading to damaged relationships and few tangible work products. It is not trivial to create a partnership culture in which the participants get along, innovation thrives and outcomes are produced.

In an earlier analysis of collaborative relationships, we found that study participants repeatedly stressed the importance of "trust and mutual respect," "being open to suggestions" and "working together" in their relationships (Catlin *et al.*, 2003). In a study of GM's private-sector partnerships, we found that study participants offered prescriptive statements about partnership behavior to ensure partnership success (Meerwarth *et al.*, 2002). Indeed, *partnership rules*, as they became articulated, accepted and followed, enabled these partnerships to flourish. From these findings we conclude that even among bright, highly-trained individuals engaged in technical research, partnership success entails relationship building and maintenance.

In this paper, we take the position that partnering relationships are part of a dynamic system that can be modeled. We saw in our earlier partnership studies that individual and partnering-organization relationships can be influenced and shaped by certain factors (e.g. "good communication," "trust," etc.), and that there are common themes and patterns, including predictability in relationships. Modeling permits us to study the inter-connectivity among these factors in partnership relationships. We prefer to view partnering relationships as data inputs that contribute to overall partnership functioning, rather than isolated entities (Winder and Judd, 1996). Viewing partnering relationships as having at least some recurring features positions us to describe, explain and learn from the system as a whole. We are then able to sort through patterns, identify best practices and recommend strategies for assimilating that learning into the entire partnership system. This new view permits us to tap into and observe partnership dynamics that have been heretofore unknown, unrecognized or unexplained.

Such modeling requires a complex tool set because of the difficulty of capturing and measuring these kinds of collaborative relationships. Our tool set, combining qualitative and quantitative analyses with a systems-dynamics approach, enabled us to conceptualize the *relationship dynamics* among partnership participants. We define relationship dynamics as the interactions associated with the collaboration process. Partnering, by its nature, involves relationships between individual counterparts, as well as relationships established between partnering organizations and/or institutions. A key dimension of partnership relationships and interactions is their reciprocal nature since relationships involve the mutual exchange of ideas, favors and the like (Sahlins, 1972). Reciprocity, the process for establishing and maintaining relationships through the exchange of goods and services, is the glue holding these partnership relationships together.

Modeling relationship dynamics in collaborative ventures makes interactions visible and thus understandable. Once understandable, managers are positioned to make judgments about the observed patterns and intervene, as appropriate, to increase the likelihood of partnership success. In our model, we seek to address the following questions about partnering relationships:

(1) What are the critical components of partnering relationships and the dependencies between components?
(2) How do these components change over time?
(3) How are these partnerships structured?
(4) How do these partnership networks evolve over time?
(5) How can partnership success be measured?

We begin by reviewing the literature pertaining to modeling organizations. Next, we discuss our data sets and methods. Working inductively, we used salient patterns from the qualitative data as input to the model, expanding the conceptualization of the model based on the social-network survey. Third, we describe the key components of relationship effectiveness – communication, joint work, quality of interaction and connectivity of social structure. We illustrate the linkages among these key components and their subcomponents, defining the basic building blocks (i.e. concepts, stocks, flows, etc.) and representing the interactive relationships. Fourth, we outline the simulation

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process we used. Finally, we generate some hypotheses from the qualitative data as we begin to validate the utility of the model.

2. Modeling relationship dynamics

2.1 Modeling organizations

Computer modeling has been popular in engineering, mathematical, computer, physical sciences and domains that are inter-disciplinary with these areas. However, using computer simulation in the social-sciences has remained an emerging area of development for some time. Historically, the first organizational models were based on administrative decision-making theories of Herbert A. Simon, from the 1940s and 1950s. This work led to the analysis of how organizational objectives are formed, how strategies evolved and how decisions are made (Cyert and March, 1963; Simon, 1944). Starting in the late 1990s, the computational modeling of social organizations and institutions became a topic of growing interest in both the computer science and social-science communities. Artificial intelligence techniques, such as distributed and learning models, were adopted to accommodate the ecological or contextual complexity of organizational relationships. Complexity theory helped in the understanding of organizational complexity from a historical perspective; organizations are affected by evolutionary events, feedback-loops and path dependencies that are critical to understanding and formalizing organizational culture and behavior (Kauffman, 1995; Waldrop, 1992).

Simultaneously, social scientists have been focusing on formalizing theories in relationships in e-business, information exchange, changes in organizational structure, authority structures, delegation, reciprocity and cooperation, empowerment, organizational evolution, and roles (Prietula *et al.*, 1998). Computational modeling of phenomena such as cooperation, coordination, dynamics of organizations and consensus formation has helped in understanding the contributing factors (Lomi and Larsen, 2001). There is now good evidence that feedback processes of mutual influence operate in social groups at multiple levels and ways, including the evolution of complex cultural behavior (Small, 1999). Understanding the relationship between organizational structures, control and cultural values is key to long-term cooperative activity (Turpin, 1999). At the same time, the dynamics of cultural influences across a social-network, where the nodes represent individuals communicating and working jointly, represents a dynamic microcosm of a knowledge network; over time, such knowledge networks can evolve into close-knit clusters of expertise (Carley and Hill, 2001).

2.2 Using systems-dynamics approach to model organizations

The term *systems thinking* is widely applied to describe a range of tools and methods used to help managers understand the inter-relatedness of organizational issues. Many of the ideas and tools of systems thinking derive from the application of system dynamics (SD) models. SD is a method for describing, modeling and simulating dynamical systems. SD was originally developed in the 1950s and 1960s at MIT by Jay W. Forrester as a set of tools for relating the structure of complex managerial systems to their performance over time, via the use of simulation.

What makes using SD different from other approaches, is the use of feedback-loops, such as those encountered in electrical and mechanical-control systems. SD concepts such as "stocks and flows"[2] describe the primary system structures and processes, and how they are connected by feedback-loops. Such loops create the non-linear characteristics of social interactions (Forrester, 1989) that are part of a systems approach to modeling. Focusing on flows and stocks of information, people and other resources has led to the exploration of complex dynamics and temporal characteristics of organizations (Sastry, 2001). When these models are applied to the social domains of organizations, the target is always a dynamic entity – changing and reacting to its environment (Richmond, 1993); it has both structure and behavior. The model itself can be represented as an equation, a logical statement or a computer program.

Basic SD models can be constructed using a simple spreadsheet program. The variables are arranged in columns and each time-step is represented in a single row. Spreadsheet models can be very helpful for understanding the linear aspects of SD models[3]. However, the group around Forrester developed the simulation software Dynamo, the ancestor of a number of modern simulation languages, to handle more complex simulation conditions. More modern SD software products followed, allowing the design of system models in a graphical mode as flow diagrams[4]. In our research and modeling, we have taken advantage of these advances to propose and test a more complex model than would be possible through spreadsheet analysis.

2.3 The gap this research fills

Our approach fills in a number of gaps in the social-science, social-network and modeling literatures. All three approaches are commonly

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used to describe business environments or simulate business conditions, but they are virtually never combined or applied simultaneously.

One contribution involves a systematic process for linking the qualitative data to baseline quantitative data at several key junctures throughout the research. Qualitative data structured the design of the quantitative research tools such as the social-network survey, the construction of the cultural model and the validation of the model. This process produced an empirically grounded set of components for the model. The findings pertaining to key behavior patterns from the qualitative analysis correlated well with the statistical analysis of survey data and sociometric analysis of the social structure data. The process of triangulating the quantitative and qualitative data is also supported by the emergence of cultural themes from study-participant quotes. Triangulation (i.e. qualitative reliability and validity processes) enabled us to conduct an internal-consistency check of the findings from one source of data (e.g. the social-network survey) by linking and cross-referencing them with data that were not collected in the same time frame or with the same technique.

We extended this iterative process when we combined social-network analysis, statistical analysis, with simulation of the model using SD software to address the structure and the dynamic aspects of organizations simultaneously.

Another gap is addressed by focusing on the evolution of the collaborative relationships over time. Most previous investigations have typically ignored the longitudinal aspects of networks.

Our model is also innovative in terms of its ability to represent the culture of an inter-organizational entity. It is able to combine genuinely diverse populations rather than focus on a single homogeneous organization. Most studies, to date, have been restricted to single-organization issues, rather than the more complicated inter-organizational collaborative partnerships.

Our creation of the concept of relationship dynamics is probably the most important and unique feature of the research. This new concept results from and affects collaborative partnerships. We created this concept to help explain the theme of reciprocity found in our qualitative data, as well as the rules, roles and collaboration themes found in an earlier data set involving GM's relationship with private-sector firms. Our research shows that many different socio-cultural components contribute to the partnering experience. We describe the four most salient components in detail as they relate to these GM research partnerships. The current version of the model focuses on relationships. In the future, we plan to expand the model to include such factors as the allocation of human resources and funding to the partnerships.

3. Data and methods

3.1 Background on sample selection

Much of the empirical foundation for our model is a study of GM R&D partnerships with five research institutions. The model comprehends the perspectives and experiences of the GM participants combined with the research-institution participants who collaborated with them.

When we began our study, four CRLs were working with GM R&D in the US. Agreements were drawn up between GM and the universities about the structure and content of the joint work, the funding designated to support university personnel, and the length of the agreement. We approached each of the Co-Directors of the CRLs to gauge their interest in participating in our study; all indicated their willingness to take part.

Because we wondered about the degree of similarity across all types of research institutions, we included a research laboratory in our sample. The employees of this research laboratory engaged in research projects, as did the university participants. In addition, the same concentrated attention in particular technical or "thrust" areas, and the designation of leadership roles within each thrust area, were also points of similarity with the CRLs. Yet, at the same time, this research laboratory added diversity to the sample because it was not a university. Moreover, GM has an equity interest in this research laboratory. We believed that crafting a partnership model from two different types of research partnerships would make our model more comprehensive.

3.2 Research design

Our research design (Figure 1) incorporated a multi-method approach to data collection and analysis; one of its outcomes was the relationship dynamics model.

Since we began our research with little knowledge of partnership structure and dynamics in the research-institution partnerships, we worked inductively. First, we created research goals with GM managers that targeted their concerns. Second, we identified those data collection techniques that we believed would yield the most useful insights. For example, we developed open-ended questions for our interviews and focus groups and built rapport with a cross-sectional sample. Third, we used salient patterns from the qualitative data as a framework for the questions on the social-network survey, and as input to an

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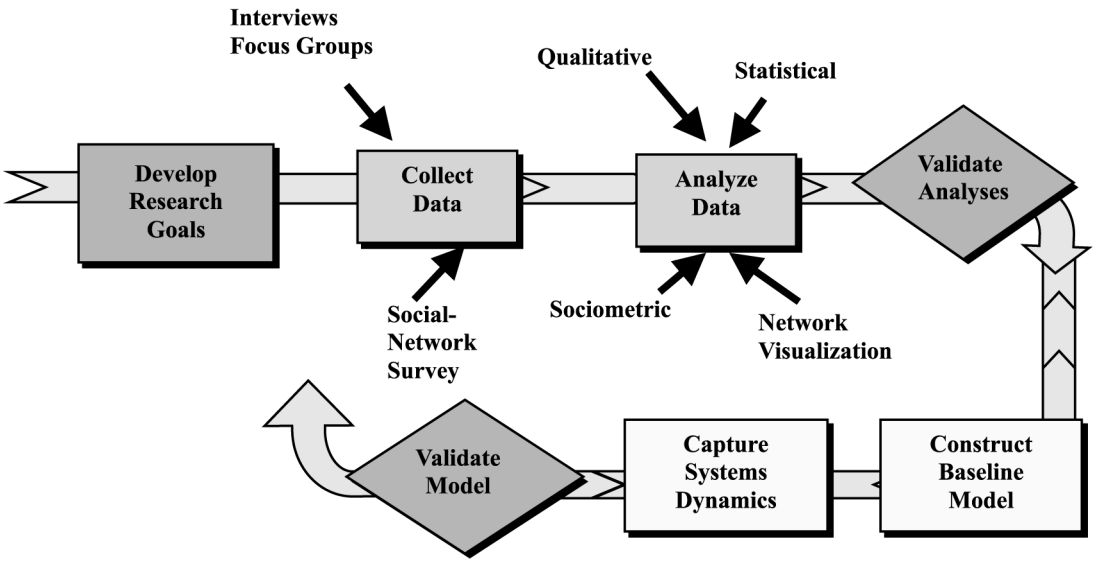
Figure 1 Partnership research design



early version of the model. Fourth, we combined the statistical and sociometric analyses from the survey data with network-visualization programs to explore the dynamics and evolutionary patterns associated with partnerships. Fifth, we validated our qualitative and quantitative results in numerous open seminars at GM R&D, the four universities, and the research laboratory.

Our next step involved constructing a baseline model to show the inter-dependencies and evolutionary potential. We used the results from both the qualitative data and the social-network survey to create the key components of the model, calculating overall relationship effectiveness as a weighted average of all components. We also relied on our data to create a hypothetical time line consistent with the stage-based insight from the qualitative data. Next, we simulated the model using a systems-dynamics approach. We generated a number of initial hypotheses from our data set and are now in the process of validating the model by re-examining the empirical data for evidence of the simulated results.

3.3 Data collection

We initiated the project by conducting in-depth interviews with 83 individuals, 47 from GM and 36 from the five research institutions; in each partnership, there were only two partners (i.e. the GM side and the research-institution side). Our interview questions focused on the nature of the participants' past and current relationships with their counterparts, perceived success factors for and obstacles confronting the partnership, institutional/organizational cultures of the partners, and expectations about the future of the partnership. Our ten focus groups had nine participants on average, combining the views and experience of over 90 individuals. The focus-group questions explored partnership goals and expectations, the participants' current assessment of the partnership, recipes for an ideal partnership and ideas for strengthening these long-term relationships.

The social-network survey was subsequently distributed via e-mail to all those associated with the five partnerships. We designed the survey to gather data on partnership structure, dynamics and roles. The survey contained questions about the respondents' roles, communication, joint work, trust, cooperation and conflict between the respondents and their counterparts, and status and decision-making of the respondents relative to their counterparts. The survey response rate ranged from 50 to 100 percent across the five partnerships. The 173 respondents produced an overall response rate of 60.5 percent, about twice the expected return rate. They provided information on 505 unique alters (i.e. people named), as well as a total of 1,597 relationship pairs (see Appendix 1 for the list of survey questions).

In Fall 2002, we conducted ten seminars or validation sessions (Kirk and Miller, 1986), attended by both those who were part of the initial data collection process and those who had not participated in the study. These sessions allowed us to present what we had learned to date, and gather input on the validity and saliency of our findings. As such, they were an opportunity to test the soundness of our analyses and interpretations, and to integrate new insights into our work. We also viewed these sessions as a way to provide

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timely feedback to those who participated or were interested in the study.

3.4 Data analysis

We followed an empirical-analysis strategy that was both inductive and comparative. For the qualitative analyses, we focused on themes and patterns that emerged from the interview and focus group data (Bernard, 1998; Schensul and LeCompte, 1999; Trotter and Schensul, 1998). These analyses entailed the

- discovery of key content elements (e.g. the structure of partnerships, the collaboration process, relationships, values, ideas, etc.); found in the interviews and focus groups;
- identification of key quotes or verbatim data illustrating important themes or content areas; and
- linkages pertaining to themes and patterns across all the interviews and focus groups.

With the qualitative analyses as a foundation, we extended our understanding of partnership structure and dynamics through several quantitative analyses based on the social-network survey. We then compared the results from our qualitative analyses with the quantitative analyses (e.g. sociometric, network-visualization, statistical, etc.) from the social-network survey.

3.4.1 Qualitative analyses

Our interview and focus-group data from both sides of the five partnerships indicated that most aspects of the collaborations were working very well. Therefore, we made an initial assumption that the structure and dynamics of the partnership relationships were generally tending towards a "typical" partnership structure, and that the network structure of each partnership could be used to represent that structure for the particular time frame or stage. We used this projected structure to create the baseline model of the existing partnership patterns.

For the CRLs, our initial qualitative analyses of the structure of the partnerships led us to create a six-stage partnership cycle. We labeled the stages Selection, Courtship, Start-Up, Mid-Term, Mature and Transition. We found that three of these stages were well matched with our social-network data – Start-Up, Mid-Term and Mature[5]. We also found that the partnership cycle associated with the research laboratory partnership was compressed compared with the CRL partnership cycle. Because the projects between GM and the research laboratory were budgeted and reviewed on an annual basis, those participants experienced all six stages in any given year. As a result of the qualitative analysis, we constructed the model with a time-based framework[6].

3.4.2 Sociometric and network-visualization analyses

Next, we analyzed the quantitative data from the social-network survey using egocentric network analysis, sociometric analysis and network-visualization techniques (Wasserman *et al.*, 1994). The egocentric analysis allowed us to compare individuals and groups with respect to communication, trust and conflict, among other variables. With the sociometric data[7], we pooled all the responses and analyzed the structure of the partnerships and the role dynamics. Graphic displays of the sociometric data revealed evidence of the time-based framework noted in the qualitative data. Through network-visualization programs, which utilize both two- and three-dimensional visualizations, we were able to compare the structural analysis of the partnership networks both within and across partnerships[8]. In particular, these programs illustrated a progression of structural complexity as we compared partnerships by age (see Appendix 2 for a complete listing of the software programs). We integrated these findings into our model by making the assumption that collaborative relationships pass through increasingly-complex stages in a partnership cycle.

3.4.3 Statistical analyses

We also analyzed the survey data statistically to generate quantitative input for the systems-dynamics elements of the cultural model[9]. We performed cross tabulations on the survey responses. Next, we pooled the GM and the research-institution participants separately and looked for patterns to characterize the partners. Then, we clustered the responses from each set of partnership participants to create a profile of the five partnerships[10]. As with the qualitative data, we made an initial assumption that each partnership represented an appropriate example for a generic partnership at that particular stage[11]. We also examined correlations between key issues surfacing between the partnering organizations. Then we used the correlations to calibrate the relationships between the components of the model, and the frequencies computed as percentages as input to simulate the model.

4. Relationship dynamics model

4.1 Rationale for the model

Our model specifies relationship effectiveness as a composite of four basic system-level components: communication, joint-work, quality of interaction and connectivity of social structure. Our rationale

for the selection of these components is based on our knowledge of the social-science literature, and analyses from our data sets on GM partnerships.

The primary input into the conceptualization of the model was the initial qualitative analysis of the interview and focus-group data from these five research-institution partnerships, along with earlier analyses of the GM's relationships with private-sector partnerships (Meerwarth *et al.*, 2002) and GM's global product program relationships (Briody, 1998; Briody *et al.*, 2004 forthcoming). For example, past observations of GM relationships with internal GM partners, and the scientific literature more broadly, indicate that partnerships routinely face conflict. Conflict emerges under a variety of circumstances including the existence of divergent technical and business goals, lack of agreement on work processes and practices, and differences in expectations about roles. Therefore, we created a subcomponent of the model that took level of conflict into account.

Following the thematic leads provided by the qualitative analysis, we then searched the business and social-science literatures for secondary data and theoretical confirmation of the components that were emerging for the model. We suspected that our preliminary selection of components would be confirmed as key concepts or concerns in a substantive keyword search of the existing business research literature. The search results[12] provided strong support for our basic assumptions, as well as individual citations on the key components highlighted in this paper. As an example, there were 236,046 citations available in the business literature on the concept of communication, 50,208 on trust, 39,133 on conflict, 36,278 on cooperation, 2,976 on organizational structure, and approximately 1,000 corresponding to our concept of joint work (based on the combination of several categories). There was also a substantive literature on the use of social-network analysis in business contexts. The content of selected articles from this search further confirmed the centrality of the components of the emerging model in the creation and maintenance of successful partnerships.

A third input into the conceptualization of the model involved the analyses generated from the social-network survey. The range of responses to each question suggested that the questions were tapping into critical partnership variables. We asked individuals to rate their relationship with each person they named in their network from lowest (or poorest) to highest (or most positive), using a six-point scale. The fact that the whole range of responses was used by at least some of the respondents indicates that we were measuring conditions that both varied within and across the partnerships, and could be critically judged by the respondents. Clearly, all relationships were not the same, or based solely on some kind of social-desirability condition. In addition, the fact that each respondent varied his/her ratings, rather than simply duplicating the ratings for all individuals they named, also indicates that we were tapping into conditions that were measurable variables in partnership relationships.

4.2 Description of the model

The complementary sources of input to the model confirmed the appropriateness of culture-level components rather than a focus on the characteristics of the respondents. Our components are necessarily composite conditions targeting system-level dynamics rather than individual dynamics. Individuals have an impact on the system on a person-to-person basis. However, these individual effects are both shaped by and filtered through cultural norms, expectations, roles and reciprocity rules. Effective system-level changes must take into account and address the culture of the entire system, rather than simply rely on individual-level change or dynamics. Therefore, the most powerful modeling and intervention opportunities for the collaborative ventures occur at the system- or cultural-level, and not at the individual- or psychosocial-level. We now turn to a description of our four key components and their critical subcomponents.

4.2.1 Communication

Our qualitative data indicate that good communication is the most frequently-cited ideal component that both parties want out of a partnership. The importance of communication is reflected in numerous statements in the interviews, and most succinctly summarized by one of the CRL thrust leaders when he stated, "Communication is the key. We need to know the GM requirements"[13]. Consequently, we collected survey data on two aspects of communication: the importance of the communication and the frequency of communication between each set of individuals engaged in the partnerships.

4.2.2 Joint work

Joint work, or the process of achieving the primary goals of the thrust areas, is both the raison d'être holding the relationships together, and the driving force justifying the establishment of the partnership in the first place. As one CRL thrust leader stated, "The most important ingredient [in a collaborative partnership] is working jointly to keep these guys interested in the program". Joint work also encourages the continued participation

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of GM and the partners in the collaboration despite difficulties during the partnership cycle. There were numerous indications in the qualitative data that the time invested in the joint work was critical, and sometimes a pressure point on the overall relationship. As one GM research manager expressed, "We should put more effort into it on our side. We set it up and put some effort in, but we aren't engaged as much. That's the danger. You can't get much out of these kinds of things unless you put the time in. Money is no substitute". Consequently, we decided to measure the perceived importance of joint work between all of the individuals surveyed and their counterparts by asking about the relative importance of joint-work activities. We also asked about the frequency of the joint work conducted between collaborating partners.

4.2.3 Quality of interaction

The qualitative data indicated that there were at least three crucial cultural themes – trust, cooperation and conflict – that have a direct impact on the quality of the interaction. Our social-network survey measured the perceived levels of trust, cooperation and conflict that existed between the survey respondents and each of the individuals they named in the social-network survey. These data provide both an individual-level and a partnership-level measure of the quality of interaction.

Trust. Participants often emphasized the importance of building and maintaining their relationships with their partners to enhance trust. One GM researcher stated, … "there has to be confidence and trust between the two groups – trust that you'll get results, and trust that the relationship will develop into a good one". In fact, trust was the most frequently-mentioned feature when quality of interaction was discussed. Therefore, we constructed a question in the social-network survey that directly measured the level of trust between each of the respondents and those they named in their partnership.

Cooperation. The concept of cooperation also emerged frequently in the qualitative data. It appeared both separately and in conjunction with the concept of trust, and therefore, became one of the key themes in the data. As one CRL researcher said, "Cooperation must be nurtured", another stated that, "The most important thing is people have to feel comfortable with each other because that certainly makes it a lot easier. You need to be able to talk to each other even if you are unhappy, and then you can try to fix it". The general use of the term cooperation, and the emphasis on positive relationships in the qualitative data, caused us to include a survey question designed as a measure of perceived person-to-person cooperation levels.

Conflict. The qualitative data generally focused on what was going well within these research-institution partnerships. However, our study participants did provide examples of periodic, temporary, or sporadic conflict. In one example, a GM researcher indicated that, "It's a forced relationship. What makes you think you can work with all those people?" On another occasion, one of the research laboratory researchers stated, "Sometimes we have those conflicts with technical directions of what's to be achieved and what's not. Then I think [of] those conflict issues, [and] we just have to have a conference … and we try to resolve those issues". Some of the conflict was due to the cultural differences between GM and the research institutions (e.g. issues of intellectual property rights, publication, patents, etc.). In other instances, conflict arose from problems associated with either structure (e.g. differences in hierarchies, institutional processes, etc.) or individual interactions. Differences between the partners can result in conflict that then impacts communication, joint work and even the structure of the relationship. The qualitative indicators suggesting that some conflict is present even in the best of collaborations motivated us to ask about the level of perceived partnership conflict.

4.2.4 Connectivity of social structure

Key individuals in the partnerships recognized the need for a complex social structure that maximized the positive components of communication, joint work and the quality of interaction, while minimizing the competition among these three components. One GM researcher explained that his partnership's success was due, in part, to his counterpart's efforts to establish and maintain connections with him and his GM colleagues. He commented, "We've gotten to know each other better. [One of the CRL leaders] does an excellent job of keeping us informed, and involved, and his faculty involved". Following this qualitative lead, we decided to examine two role variables that express the key structural components of the relationship. The components chosen to construct this segment of the model include role dynamics expressed as fragmentation and reach, and structural components expressed as network density, transitivity and betweenness-centrality.

Role dynamics. The role dynamics portion of the model consists of one positive and one negative force within the sociometric data.

(1) *Fragmentation*. We define fragmentation as a measure of the amount of dislocation of individual connections in the network caused by the removal of "key players" (i.e. central figures in a partnership) and their connections to others. Fragmentation can be conceptualized as the creation of individual islands or clusters of

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relationships with no bridge between them; as such, it acts as a negative force in the sociometric data. Researchers and managers in these partnerships acknowledge the tendency of the collaboration to fragment over time. Such a pattern makes the issue of fragmentation central to the structure and dynamics of collaborative partnerships. One CRL research manager commented, "There's a very natural tendency for two institutions to set up a collaborative project and then have that collaboration naturally fragment or naturally segment". We were able to measure the impact of fragmentation in the model by removing key players from the overall structure of the partnership. We could then determine the impact of that removal on other components in the model.

The impact of fragmentation is shown in Figure 2 when one or more key players are removed from the partnership. It shows a small network (Configuration A) initially connected by two key players (1 and 8). The loss of key player 8 (Configuration B) means that the subunit represented by individuals 9-12 is no longer connected to the whole; the network is fragmented. In contrast, the loss of key player 1 (Configuration C) translates into a much less effective configuration of the partnership at the core. This condition leads to longer communication lines between all individuals, though all of the individuals in the network are still connected, that is, they are not fragmented. Both of these conditions are important in understanding the impact of the loss of key players in any given partnership.

(2) *Reach*. A second role-based dynamic expressed in the qualitative data is the need for individuals who can communicate and reinforce the primary goals of the partnership to the maximum number of network partners. Reach is a positive force in the sociometric data. The need for good reach is alluded to in the following CRL researcher statement:

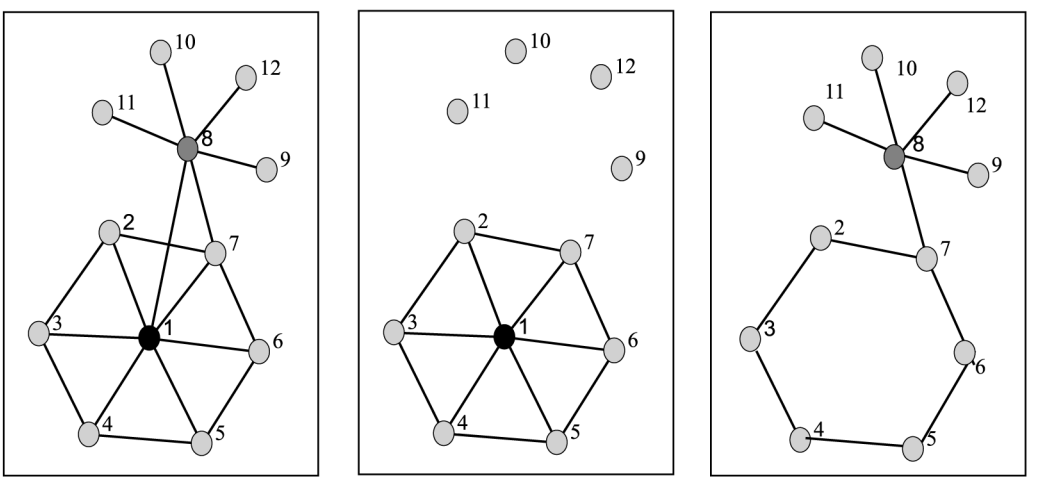
> He sees his job as director to clearly articulate the long-term goals, to clearly articulate the directions that we want people to go on, but then, to not tell people what to do [which might restrict creativity] – to essentially tell them where we want to get and provide the freedom for them to actually get there in the best way they can.

Consequently, we used a measure of reach to identify the key individual or individuals linked to as many distinct partnership participants as possible. Reach provides a measure of the proportion of the total network that a single individual is either in direct or indirect contact with at a given point of time. In Figure 2 (Configuration A), key player 1 can easily contact and/or influence either the whole network, or major parts of it, directly or through a minimum number of intermediates. The partnership-network data indicate that participants have different levels or spreads of reach, depending on the size and complexity of the partnership as it changes over time.

Structure. We used basic sociometric analysis of the social-network survey data to compute three subcomponents of the partnership networks that help define the structure of connections and connectivity in the partnerships. These components include density, transitivity and betweenness-centrality.

(1) *Density*. Density provides a measure for the overall amount of "connectedness" in a network.

Figure 2 Examples of fragmentation potential of key players[14]



Source: Adapted from Borgatti (2003, p. 242)

This measure is derived by counting the total number of connections that exist between people in a group, and then counting the total number of possible connections. Dividing the existing connections by the potential connections produces a number that identifies the proportion of all existing ties among individuals to all potential ties. The higher the number, the denser is the network. When the network is dense, it provides more opportunities for alternate routing through the network in case of a failure of one or more links. One GM researcher stated it this way, "The partnership has become much stronger and it's more synergistic and intertwined. We consider it our responsibility that the work (of the different CRLs) is complementary and synergistic". Density translates into a more stable structure for the whole network. It also reduces the problems that occur when someone is removed from the network, thereby resulting in a loss of connections. In Figure 2 (Configuration A), the core group connected by the key player 1 has a higher number of actual relationships compared to possible relationships. Therefore, this core group is denser than the subgroup of key player 8; the latter has fewer total connections compared with potential connections.

(2) *Transitivity.* Transitivity is a sociometric measure that identifies the proportion of triples (i.e. three people all connected to each other) that are connected, compared with the potential total number of these triples. It provides a measure of the connections between the individuals who are connected to a central person, rather than a simple measure of all connections. The need for this measure was captured in a quote from a GM participant who praised the ability of one of the CRL partners to make these kinds of connections between individuals: "During the [joint meetings], he [the CRL partner] does an excellent job of presenting to us, bringing in others from outside his department, and that has led to some relationships [with those other departments and individuals]". Transitivity is similar to density in that it provides another way of examining the overall connectedness and stability of a network. Referring again to Figure 2 (Configuration A), key player 1 is part of several triples (e.g. 2-1-7, 4-1-5) in which three people are connected to each other. These triples are examples of transitive relationships. By contrast, key player 8 has one transitive relationship (i.e. 1-8-7), and that subgroup in the partnership has a lower transitivity value than the core group of key player 1.

(3) *Betweenness-centrality.* Some individuals occupy central positions in a collaborative network. Consequently, they become key linkage points for good communication flow to either part or all of the network. These individuals exhibit a condition that we label "centrality." One GM leader working with the research laboratory partnership described this type of centrality in information flow in the following statement: "The most frequent contact is the PI [Principal Investigator] to the [GM] Champion, and a lot of the communication goes along there (and out to others)". There are several different sociometric forms of centrality. We chose to use betweenness-centrality, which is formally defined as the number of times a vertex occurs on a geodesic[15]. Figure 2 shows that key players 1 and 8 exhibit the type of centrality that is expected of a GM Champion or PI. Individuals in these types of positions typically control the flow of information, influence others and/or hold the network together.

4.2.5 The relationship dynamics model

The overall connections between the four key components of our relationship dynamics model can be illustrated as an interactive web. Each of the four components, in turn, is a composite of relationship subcomponents that further define behavior and interactions. We illustrate the model in Figure 3.

5. Simulating relationship dynamics

5.1 Basic building blocks to represent the model

We hypothesize that each of the four system-level components – quality of interaction, social structure, joint work and communication – contributes differentially to relationship effectiveness in these collaborative partnerships. Representing relationship effectiveness in a model requires taking into account the varying levels of interactions and feedback. At any particular time, relationship effectiveness is an aggregated outcome of these four components and any subcomponents. In turn, each component impacts and is affected by the composite relationship effectiveness and the varying levels of the other composite components. We are in the process of validating the model with existing qualitative data, reviews with study participants and results from a follow-up survey.

Systems-dynamics is a standard way to examine the interactions among the components of the model and the evolutionary change at the system-level. In a systems-dynamics framework, each of the components has both positive and negative effects on each part of the system and the system as a whole. This framework enables an investigation of the non-intuitive dynamics among the key components. A systems-dynamics approach has the ability to represent the emerging behavior of

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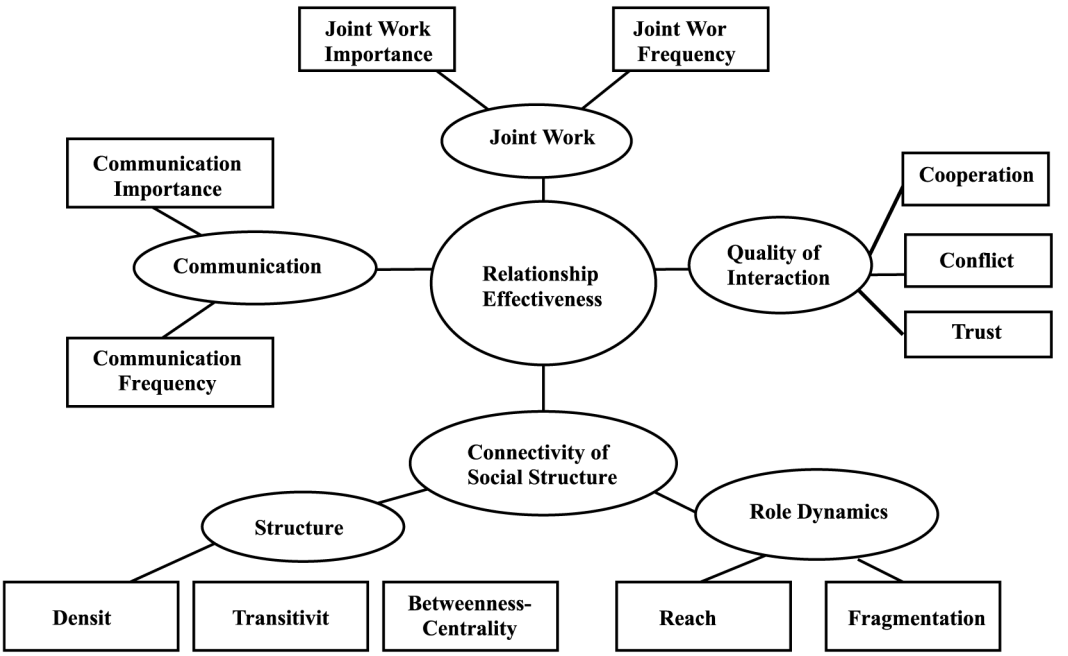
Figure 3 Relationship dynamics model

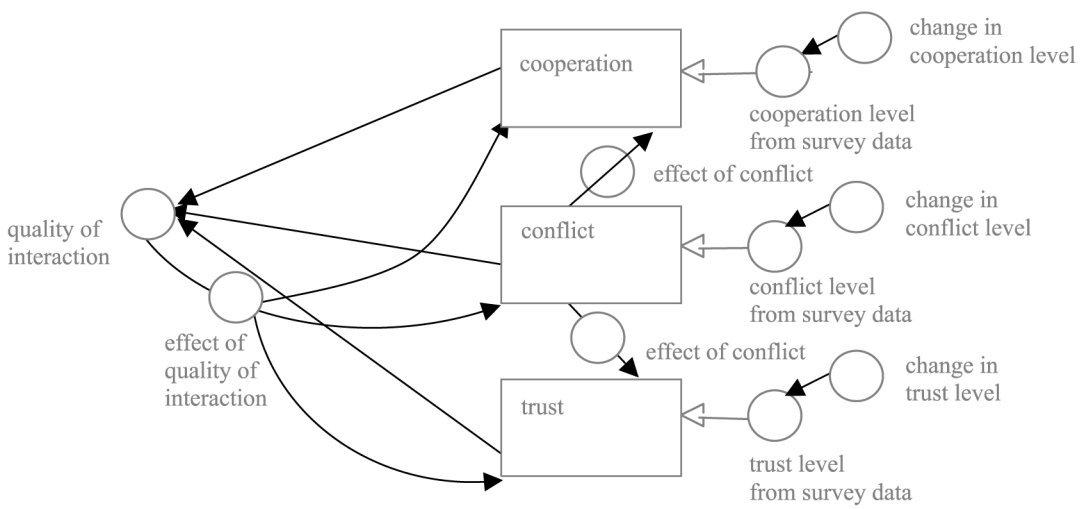


interacting loops (i.e. balancing, reinforcing or draining feedback), the ability to represent non-linear effects, and the use of continuous-time representation. In addition, by tracing through the feedback-loops, we can explore the evolutionary processes over time (Sastry, 1997, 2001). Thus, it has the potential to lead to new hypotheses, research questions and extensions of the current model.

In Figure 4, we show how we visualize quality of interaction. We represent it using cooperation, trust and conflict as the building blocks.

These three subcomponents are represented as rectangles (or "stocks" in systems-dynamics terminology), which are "stocked" by (i.e. accumulate or contain) the survey data that flow into them. Levels in these stocks vary over time based on various direct and indirect forces. "Flows" represent the actions or activities over time. We can change the levels of stocks via "converters" (depicted as circles) that represent relationships as mathematical equations. Trust, conflict and cooperation are linked (indicated by thin arrows, and referred to as "connectors" in systems-dynamics terminology) to form a composite component in the diagram – in this case, quality of interaction. Quality of interaction is represented as a "converter," an element that

Figure 4 Example of representing components of the model as stocks and flows[16]



converts these inputs into an output, which then leads to the other components of the model.

There are also feedback-loops (shown as thin loops) that represent feedback or causality from increasing and decreasing levels of conflict on cooperation and trust to the other components. Quality of interaction, which represents the intertwined set of interdependent relationships between cooperation, conflict and trust, in turn affects the levels of these and other key components. We represent these cause-and-effect relationships with the loops and converters. Because relationships are neither static nor linear, we illustrate the model as a closed-loop; dependent and interdependent variables become part of a web of interrelationships.

5.2 Simulating the model

Our first round of qualitative and survey data enabled us to conceptualize the model, identify the four key components, and conduct some initial validation. As such we feel that we have a proof of concept. However, because of our current data limitations (e.g. the current data represent only one point in time), we make some initial assumptions in developing the model. We describe these assumptions below, anticipating that some will be relaxed and/or revised based on our follow-up survey to participants in these partnerships. In particular, this follow-up survey will provide us with data at a second point in time, and increase the sample size from five partnerships to nine. In later analyses, we also will examine the partnerships by technical or "thrust" areas. Thus, the second survey responses added to the initial data will enable us to estimate the model parameters more accurately and increase confidence in the simulations involving dynamics.

The partnerships from our first round of data collection were at different stages in their partnership life cycle when we collected the survey data. As indicated earlier, we used the survey data to create a hypothetical five-year timeline, with each partnership representing an example of a generic partnership at that particular stage of development[17]. We then used this assumption to develop a baseline composite partnership over a five-year time frame. We normalized the data to accommodate differences in the number of respondents associated with each partnership.

Since our youngest partnership was in its first year, the initial stage depicted in the model is the first year; we label it the Start-Up stage (Section 3.4). Organizational theory indicates that at the beginning, organizations have low inertia – meaning young organizations can change easily but the performance levels are low (Sastry, 2001). This baseline condition matches well with the qualitative data that we collected about the start-up processes for each of the collaborations. Data from a partnership 1.5 years into the partnership cycle represent partnerships towards the end of the Start-Up stage. The Mid-Term stage is represented by a partnership that was two years old at the time of the survey. Finally, two partnerships were at years 3 and 4, which were associated with the Mature and Late Mature stages, respectively. We know from the qualitative data that each partnership stage is depicted with particular attributes and issues.

5.2.1 Simulation procedure

We initialized the stocks in the model with data from the social-network survey to represent different levels of interaction among participants. We picked the data values at the 5th, 50th and 95th percentile ranges to represent low, average and high levels for all of the components[18]. We also calculated the survey values as percentages for the role dynamics and connectivity components (i.e. density, transitivity, centrality fragmentation, reach, etc.) using network role programs (e.g. Key Player), and basic sociometric programs (e.g. UCINET X); we calibrated the stocks corresponding to these components.

To model the dependencies in the system, we constructed the underlying pattern from the correlations between the key components observed in the statistical inferences in the survey data. We calculated the composite values as a weighted average of the contributing components that include these correlations. Because the model's components interact with each other directly, the components cannot be viewed independently (Reaume and Alden, 2002). For example, if a component like trust is increased, overall relationship effectiveness is improved; indirectly, other components and subcomponents are also likely to be enhanced, further improving the entire relationship.

Despite the sampling limitations, we were interested in the potential use of the model as a predictive tool. Therefore, we calibrated the model by setting the appropriate parameter values and functional relationships consistent with the changes observed in the partnership cycle. We chose Euler's method to estimate the change in stocks over the interval dt.

$$\Delta\text{stock} = \mathrm{d}t \cdot \text{flow}$$

where flow is the rate of change corresponding to the stage in the partnership cycle.
We calculated a new value for stocks based on this estimate:

$$\text{stock}_t = \text{stock}_{t-\mathrm{d}t} + \Delta\text{stock}$$

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We compared the approximations with our baseline partnership behavior. Then we set the simulation time-step (dt) to 0.25, where the unit of time is a year corresponding to the stage in the partnership cycle. This time-step sets the interval of time between calculations to 1/4th of a year, which seemed feasible and sufficient to simulate the pattern observed from the empirical data.

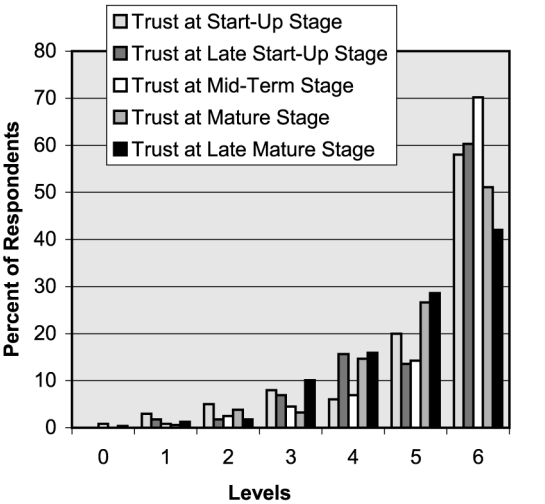
Using regression, we calculated the flow rates (i.e. a temporal feature derived from the survey data) to reflect how composites might behave over time. This rate of change was determined as the slope of the best-fit line between the baseline-model data points. We initialized the model to steady-state, representing an organization that is not experiencing change. Then, we started varying the levels of stocks one by one, while observing the effects on the composite components. We then generated several hypotheses to begin to test the model.

5.2.2 Understanding effects: examples of trust and conflict

In this last section of the paper, we wanted to begin to examine the utility of the relationship-effectiveness model. Therefore, we returned to the qualitative data to generate an initial list of hypotheses about the components and the ways in which they were connected. It struck us that some of the more interesting aspects of the partnering relationship pertained to trust and conflict. We heard repeatedly, for example, that without trust, the relationship would not be successful in the long-term. Indeed, interviewees indicated that trust was a necessary condition for partnership effectiveness. By contrast, interviewee stories suggested that when conflict erupted, it could be quite potent, though not necessarily long-lasting. Moreover, when we examined the correlation between the level of trust and conflict respondents expressed for the counterparts they named, we found a negative correlation (~ -0.4) at the individual-level. Thus, in this section, to illustrate the model's utility, we will focus our discussion on these two subcomponents of quality of interaction.

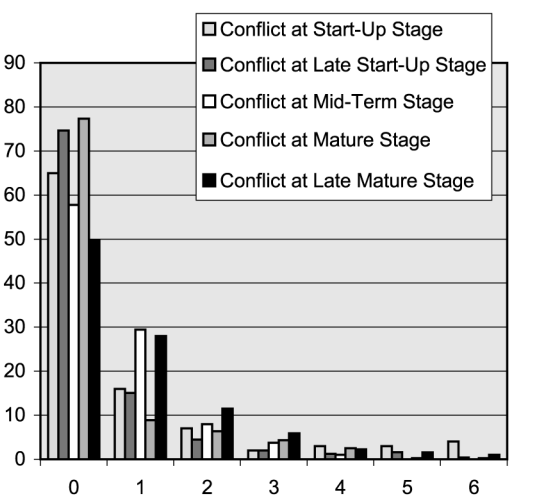
Comparison of trust and conflict. From our qualitative interviews we learned that trust was one of the most frequently-mentioned elements needed in a collaborative relationship. One GM research manager remarked that, "There is always this trust hurdle you have to get by. In an ideal partnership, you would achieve a workable-level of trust very early on". Figure 5 summarizes the frequencies of the survey respondents' ratings pertaining to trust. We use a scale of 0 to 6, where 0 indicates the lowest level of trust and 6 indicates the highest level of trust. Most respondents' trust rate high, either as 5 or 6 on the rating scale. However, at least some participants in the partnerships have very low levels of trust with at least some of the people they named. Indeed, during the Start-Up phase, some significant trust issues appear (e.g. intellectual-property rights, number and type of reviews, etc.).

Figure 5 Levels of trust on a scale from 0 to 6



The survey data also indicate that conflict levels are low in these partnerships. Figure 6 shows how the overall ratings of conflict vary over the partnership cycle. As with trust, we used a scale of 0 to 6, where 0 indicates the lowest level of conflict and 6 indicates the highest level of conflict. Low conflict may be a sign of the potential for success in these partnerships – at least from the standpoint of the relationships among participants. Conflict, while low, is an important dimension of these partnerships. Two quotes – one from a university researcher and one from

Figure 6 Conflict level ratings on a scale from 0 to 6



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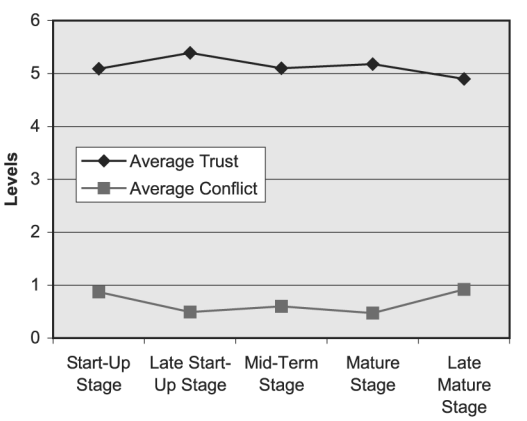
a GM researcher – illustrate two different perspectives on the direction given to and management of the CRL work. The university researcher said, "We can't have GM coming in telling us what to do. The final decision on the scope of the work has to be with the faculty". The GM researcher expressed it differently: "I get the feeling from [the university] that this CRL is a part-time endeavor for them... They are willing to do it but on their time... You [GM] have to talk or hold back money to get accountability from the universities". Comments like these clearly indicate a difference of opinion or a difference in expectations between the partners. If such a difference is not discussed and addressed, it could expand to encompass other issues and result in increasing conflict.

Figure 7 compares average trust and average conflict over the partnership cycle. This figure shows some interesting patterns. First, survey participants' scaled responses show the remarkable contrast between trust and conflict in these five partnerships: trust is very high and conflict is very low. This pattern confirms much of our qualitative data that these partnerships, as a whole, are working well. A second pattern that emerges is that trust is largely the mirror image of conflict. While the differences between the partnerships are small, the correlation between trust and conflict holds not just at the individual-level, but at the partner-level as well.

Finally, the scaled responses suggest that the patterns for these two subcomponents are relatively stable over the course of the partnership cycle with only some variation by stage. For example, conflict is somewhat higher at the start and the end of the partnership cycle compared with the middle stages of the cycle. We know from the qualitative data that the initial stage of the cycle is stressful for participants because they are trying to develop relationships, agree on their project goals and create a process for working together.

Figure 7 Average trust and conflict in partnership cycle



Similarly, the end of the cycle is associated with some increased conflict because there is uncertainty about renewal – whether of individual projects as in the case of the equity partnership, or collaborative labs as in the case of the university partnerships. Yet, even with this slightly elevated level on either end of the partnership cycle, the relative stability is an indicator of evenly-balanced relationships.

Hypotheses. While we believe that both trust and conflict can have wide-sweeping effects on the overall partnering relationship due to our qualitative results, we are currently unable to test these effects due to data limitations. However, we are able to examine how trust and conflict can impact other components or subcomponents in the model directly by looking at individual differences within each partnership. For example, from the qualitative data, we found that some of the relationships between individual counterparts got off to a rocky start during the Start-Up phase. For example, issues emerged as goals and procedures for joint work were established. In one case involving the late Start-Up partnership, some within the CRL expressed concerns that GM was attempting to direct their research focus. Since these concerns continued to be expressed over many months, we hypothesized that low trust resulted, which then led to low communication frequency. A cross-tabulation of trust and communication frequency from the survey data indicated that this hypothesis was supported.

In another example from the qualitative data involving an early Start-Up partnership, we learned that there were concerns on both sides of the partnership that GM researchers had insufficient time to devote to their partnership work. Therefore, we hypothesized that those reporting low levels of joint-work frequency would report higher levels of conflict during Start-Up. When we performed cross-tabulations on the survey data, we found support for this hypothesis as well.

To complement these Start-Up hypotheses, we decided to focus on the quality of interaction in a later stage of the partnership cycle. We thought it would be interesting to explore the relationship between conflict and cooperation in GM's research laboratory partnership compared with the four university partnerships. We suspected that those in the GM research laboratory partnership would have to take, and be more willing to take, direction from GM due to the equity relationship than would those in the university partnerships. Of course, in any of these five partnerships, conflict could arise (e.g. due to differences in expectations, disagreements over technical issues, etc.). However, we suspected that cooperation was likely to vary between the equity (i.e. research

laboratory) and non-equity (i.e. university) partnerships. Therefore, we hypothesized that even if conflict were high for the participants in the equity partnership, their cooperation would be high. By contrast, if conflict were high for participants in the CRL partnerships, their cooperation ratings would be low. Cross-tabulations of conflict and cooperation from the survey data showed a distinct difference in the pattern: those working on GM and its equity partner's projects who reported high conflict still reported good cooperation, while partnership cooperation was low or non-existent among those who reported high conflict in partnerships involving GM and the CRL universities.

In our follow-up survey, we will continue to focus on the structure and dynamics of GM research-institution partnerships. We will use the follow-up survey data to explore whether or not the differences we observe across and within partnerships are due to distinctive aspects of a given partnership, or due to the evolutionary process inherent in the partnership cycle. We also will add recently-created partnerships to the sample which will both increase our sample size and add more diversity.

6. Conclusions

6.1 Enhancing partnership success

- Partnering, an increasingly-popular business strategy, links organizations and institutions together to collaborate on projects, build competencies and enhance competitiveness. Yet partnerships exhibit a high rate of failure, typically caused by organizational and cultural differences between the partners. Identifying ways of reducing the incidence of failure and increasing the likelihood of success will have enormous benefits for the partnering organizations.
- Partnership success is largely dependent upon the development and maintenance of strong, productive relationships between the partners. Without strong relationships, there is neither a commitment to the partner nor the likelihood of achieving partnership goals.

6.2 Modeling relationships

- Partnering relationships are part of a dynamic system that can be modeled. Relationships can be influenced and shaped by certain factors, and analyzed for common themes and patterns. The modeling results can be used to diagnose and predict partnership differences. Interventions can then be designed and implemented to improve partnership effectiveness.
- Modeling partnering relationships is complicated because they are complex cultural interactions, and because they change over time. To increase the likelihood that the resulting model is realistic, valid and representative, a systems-dynamics approach can be combined with empirical data, and then validated with feedback from study participants. Systems-dynamics is used to study the interactions among the components of the model and to explore their evolution.
- Partnerships go through stages in predictable ways that can be captured in a dynamic model. Although the concept of a stage-based partnership cycle came from the qualitative data, partnership stages can be applied directly to the social-network survey data, supporting our initial findings of partnership evolution.

6.3 Developing model components and hypotheses

(1) Four key components of relationship effectiveness emerged from the analysis of the qualitative data and social-network survey – communication, joint work, quality of interaction and connectivity of social structure. These components and their associated subcomponents became the foundation for the relationship dynamics model.
   - Joint work is composed of both the frequency and importance of joint activities.
   - Quality of interaction is constructed from the values associated with three key cultural themes and processes: trust, cooperation and conflict.
   - Communication is composed of the frequency and the importance of communication with each partner.
   - Connectivity of social structure includes two subcomponents: structure and role dynamics.

   Independent theoretical justification for these components and subcomponents, derived from a search of the business research literature, confirmed their centrality in the creation and maintenance of partnerships. At any particular time, relationship effectiveness is an aggregated outcome of these four components and subcomponents, their interaction effects, and any change over time.

(2) In examining two subcomponents – trust and conflict – over the course of the partnership cycle, the pattern was relatively stable by stage, though the start and end of the cycle tended to be more stressful than the middle stages. Interestingly, trust and conflict were negatively correlated: trust was very high and conflict was very low. This pattern confirms much of our qualitative data that these partnerships, as a whole, are working well. In addition, trust was largely the mirror image of conflict, indicating that the correlation between trust and conflict holds at the partner-level as well.

(3) An initial list of hypotheses was generated from the qualitative data to begin testing the model's utility. One hypothesis, for example, was that conflict and cooperation would vary by type of research-institution partnership (i.e. equity vs university). Cross-tabulations of conflict and cooperation from the survey data showed a distinct difference in the pattern: those working on GM and its equity partner's projects who reported high conflict still reported good cooperation, while partnership cooperation was low or non-existent among those who reported high conflict in partnerships involving GM and the CRL universities.

Notes

1 The GM-Isuzu Motors Ltd relationship, dating to 1971, began with "simple technology exchanges" but now "extends to all phases of automaking – from development through sales" (Isuzu, 1998, p. 26).
2 Stocks are reservoirs for the values that define the primary elements in the model. Flows are the connections that indicate the impact or relationship between one stock and another.
3 I-Think, a web-based survey program, also can be used for initial analysis of data in tabular formats.
4 STELLA from High Performance Systems, Inc. is a SD software which enables creating models of structural stock-flow-diagrams and time-series analysis. Powersim by Business Simulation Company, and Vensim by Ventana Systems, Inc. are other available SD modeling software.
5 We did not have social-network data on the Selection, Courtship or Transition stages.
6 Currently, we are collecting sociometric data on the Courtship and Transition stages in our follow-up survey, and will extend the model into these stages. The Selection stage will be based only on the qualitative data.
7 We used several network programs, including ego-network programs (MULTINET, FATCAT), network role programs (Key Player) and basic sociometric programs (UCINET X) to conduct the egocentric and sociometric analyses.
8 Three programs were particularly valuable for the visualization analysis: PAJEK, NETDRAW and MAGE.
9 We used SAS and SPSS Statistical Software to obtain the descriptive statistics.
10 A report on the main findings of the survey analysis is in process.
11 We acknowledge the need to separate the effects of individual partnership differences from stage-based effects of the partnership cycle (and are conducting a follow-up survey to address that issue).
12 We used an online search engine, EBSCO's Business Source Premier, for the basic key word search.
13 The italicized statements in the paper represent direct quotes from our qualitative data.
14 This figure is adapted from Borgatti (2003, p. 242).
15 In this case, the vertex is a key player with strong communication capability since he/she can reach so many so quickly in the network.
16 This figure is adapted from Richmond (1993).
17 We felt reasonably comfortable making this assumption because our qualitative data suggested that the older partnerships, at one time, experienced the kinds of processes and tensions currently facing the younger partnerships.
18 We plan on adding more granularity in specifying input levels as we develop extensions to the model, which will comprehend components that are not relationship specific.

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Appendix 1. Social-network survey

Your Name_____
Your Organization_____
Your Position Title_____
Date_____

Q1. Please name your GM Partnership_____
Q2. What is your role on the partnership?_____
Q3. What is the name of your project(s) in this partnership?_____
Q4. Have you had experience working with other collaborative partnerships (any organization)? Yes_____ No_____
Q5. Please name all of the people you have a relationship with as part of your partnership (named in Q1). Use full name if possible.
Q6. Put GM if the person works for GM. Put partner if the person works for the partner.
Q7. Please indicate the formal relationship between you and the person named.
1 = peer
2 = someone who has lower rank or status compared to you
3 = someone who has higher rank or status compared to you
Q8. Does your relationship with the named person pre-date the initiation of the partnership?
1 = Yes, it predates the start of the partnership.
2 = No, it began with or after the partnership
Q9. Using a scale of 0 to 6, where
0 = none
1 = lowest
6 = highest
Please rate the frequency that you communicate with this person compared with the others on your list.
Q10. Using a scale of 0 to 6
0 = none
1 = lowest
6 = highest
Please rate the importance of the communication with this person.
Q11. Using a scale of 0 to 6
0 = none
1 = lowest
6 = highest
Please rate the level of trust you have for this person.
Q12. Using a scale of 0 to 6
0 = none
1 = lowest
6 = highest

Please rate the frequency that you work with this person compared with the others on your list.
Q13. Using a scale of 0 to 6
0 = none
1 = lowest
6 = highest
Please rate the importance of work you do with this person.
Q14. Using a scale of 0 to 6
0 = none
1 = lowest
6 = highest
Please rate the level of cooperation that exists between you and this person.
Q15. Using a scale of 0 to 6
0 = none
1 = lowest
6 = highest
Please rate the level of conflict you have with this person.
Q16. When decisions are made, which of the following describes the normal pattern, in relation to the named person?
0 = No decisions need to be made in this relationship.
1 = You normally make the decisions in the relationship.
2 = The decisions are normally joint decisions.
3 = The other person is normally responsible for making the decisions.

Appendix 2. Social-network analysis software

2.1 Analysis programs

ANTHROPAC is a cognitive anthropology data-management and analysis program. It accepts qualitative/nominal level data, as well as several forms of quantitative data, including survey instrument construction. The primary analysis routine utilized for this project was the free listing data project. Data are input in the form of individually generated lists of items from cultural domains – in this case, partnership relationships. These lists are converted to either similarity or distance matrices, and can be analyzed within the program using a wide number of statistical routines. The standard output for the free listing routine includes a saliency list of named individuals, simple descriptive statistics and both person-by-person and item-by-item output data sets that can be further analyzed (Table AI).

UCINET is a social-network analysis tool. Data can be imported or directly entered in a number of different formats. UCINET data analysis routines include most of the standard sociometric measures of network structure and dynamics including:
(1) cohesion (e.g. distance, reachability, point connectivity, etc.);
(2) regions (e.g. components, k-cores, etc.);
(3) subgroups (e.g. cliques, k-plexes, factions, etc.);
(4) centrality (e.g. degree, closeness, betweenness, etc.);
(5) ego networks;
(6) core-periphery;
(7) roles and positions; and
(8) whole network properties (e.g. density, transitivity, etc.).

Key Player imports UCINET data and performs three basic analyses. The first two analyses are based on the removal of one or more key nodes. They provide the level of impact on the network based on the fragmentation caused by the removal of the key player(s), and the increase in average distance between nodes caused by the removal of the key player(s). The third analysis identifies the overall reach of one or more key players, depending on the number of edges that connect them to other people.

NETDRAW imports UCINET data files and provides an optimized two-dimensional display of the network nodes (people) and edges (connections), including the directionality of the connections. The program allows for a visual analysis of several key attributes of the network data, including:
(1) isolates;
(2) components;
(3) blocks and cutpoints;
(4) k-cores; and
(5) subgroups.

The program also allows several different kinds of transformations of the shape of the data, including circle layouts, Grower-metric-scaling layouts, node-repulsion layouts, as well as deleting isolates and pendents – isolates are those not connected to others whereas pendents are those with only one path to the network.

MAGE is a network-visualization program. It creates a three-dimensional kinetic image that can be interactively rotated from any point of reference (node) within the matrix. The program allows different attributes of nodes and edges to be color coded, to assist in visualization analysis.

FATCAT is an egocentric data-analysis program. It analyzes two-mode (actor by attribute) data using a variety of statistical routines.

Table AI Network data sets and tools for network analysis

Data set	Nature of data	Tools	Analysis strategy	Significant findings
Freelist data	List of individuals named by each respondent	ANTHROPAC	Freelist analysis	Salience of individuals by CRL and as a whole
Aggregate ego network	SPSS data matrix constructed from survey responses	SPSS	ANOVA GLM correlations	Significant differences in individual and group relationships based on key components
		FATCAT	Cluster analysis	
Aggregate alter network	SPSS attribute data matrix constructed from survey responses	SPSS	ANOVA GLM correlations	Significant differences in individual and group relationships based on key components
		FAT	Cluster analysis	
Edgelist data sets	Converted to person by person matrix data in UCINET	UCINET V	Sociometric analysis	Structure of relationships
UCINET matrix data	UCINET data sets imported into Key Player and NETDRAW	Key Player	Fracture distance	Fracture points (transitions)
		NETDRAW	Reach cut points	Distance reach
UCINET matrix data	UCINET data imported into network visualization programs	NETDRAW	Network structure visualization analysis	Network structural change through time
		PAJEK		Key Player effects
		MAGE		