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Network Goal Analysis of Social and Organizational Systems:

Testing Dynamic Network Theory in Complex Social Networks

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Abstract

Grounded in dynamic network theory, this study examined network goal analysis (NGA) to understand complex systems. NGA provides new insights by inserting goal nodes into social networks. Goal nodes can also represent missions, objectives, or desires, thus having wide applicability. The theory ties social networks to goal nodes through a parsimonious set of social network role linkages, such as independent goal striving, system supporting, feedback, goal preventing, supportive resisting, and system negating (i.e., those who are upset with others in the pursuit). Moreover, we extend the theory's system reactance role linkage to better account for constructive conflicts. Two complex systems were examined: A team's mission and an individual's work project. In support of dynamic network theory, using the Quadratic Assignment Procedure, results demonstrated significant shared goal striving, system supporting, and shared connections between goal striving and system supporting. These findings manifest what we coin as multipendence: Systems having some actions independently involved with goals, while others are dependently involved in the associated network. NGA also demonstrated that the goal nodes manifested strong betweenness centrality, indicating that goal striving and feedback links were connecting entities across the wider system. Strategies to plan network goal interventions are illustrated with implications for practice.

Keywords

Social networks, goal pursuit, interventions, organizational development and change, network science, multipendent systems, netgoal theory, netgoal analysis, and complex systems.

Trying to understand and change complex systems in social and organizational settings has been a prominent goal for many scholars and practitioners (Battilana & Casciaro, 2012; Burke, 2014; Lewin & Cartwright, 1951; Pickering & King, 1995). Although social network analysis (SNA) provides one of the most revolutionary new ways to describe and analyze complex social systems with advanced technologies (Borgatti, Mehra, Brass, & Labianca, 2009; Contractor, Wasserman, Faust, 2006; Burt, Kilduff, & Tasselli, 2013; Lazer et al., 2009; Newman, 2003; Watts, 2004), it has not sufficiently examined how social networks are precisely connected to target goal pursuits. In response, dynamic network theory was created to help fill this void (Westaby, Pfaff, & Redding, 2014). In the founding theory, this framework explains how social networks are involved in target goal and behavioral pursuits and related phenomena (Westaby, 2012). Methodologically, the theory employs network goal analysis (NGA), grounded in the theory's core constructs, to show precisely how entities in the social networks are connected to goal nodes (Westaby & Shon, 2017). Goal nodes represent a host of targeted outcomes, such as goals, missions, objectives, or desires. Hence, the approach is scalable to any type of goal at any level of goal pursuit: individual, team, organizational, or international.

However, empirical research testing central propositions from the theory with advanced computer analytics and visualization has been lacking. Thus, the purpose of this study is to use newly advanced survey tools and computer analytics to test key propositions from dynamic network theory. We will also advance how feedback linkages about goals are used in NGA as well as demonstrate a more applicable assessment of system reactance linkages as constructive relations during conflicts. Methodologically, we will use NGA to examine two network systems involved in goal pursuit: A team's goal to accomplish its mission and an individual's goal to complete important projects.

Dynamic Network Theory

Dynamic network theory (DNT) connects entities in social networks to goal nodes through eight *social network role* linkages. The first role, *goal striving* (G), represents entities independently working on critical goal(s), such as on their own or by themselves. A person working alone on an activity is a basic example (Locke & Latham, 2002). Second, *system supporting* (S) illustrates actors helping or supporting others in the goal pursuit (Rhoades & Eisenberger, 2002). S linkages illustrate the social interdependence needed to help achieve goals, thus lending itself adeptly to traditional SNA. In combination, these two roles represent *network motivation* (aka goal pursuit links) in the system (Westaby et al., 2014). These links jointly explain how systems are joining to attain goals, wishes, or desires.

The next set of role linkages explicitly account for conflict dynamics in the context of the given goal pursuit under study. *Goal preventing* (P) illustrate actors independently obstructing or resisting the target goal. This can be seen when competitors are working independently, on their own, to gain advantage – a key concept to account for in organizational research (Ingram & Yue, 2008). *Supportive resisting* (V) occurs when dyadic relationships are obstructing or resisting the goal. For example, this can be seen when a competitor is receiving support from another, who is trying to help the resistance. *System negating* (N) represents actors feeling upset with others that are involved with the goal, such as an employee's spouse being upset with the employee pursuing overtime. We broadened this concept slightly from the original theorizing to more broadly capture dyadic conflict relations. The *system reacting* (R) role illustrates people trying to constructively react to others having conflicts with the goal. For example, the employee above may try to constructively respond to the upset spouse. This new "constructive resistance" modification is important because it recognizes that cooperative orientations to others can exist during conflicts or disagreements (Deutsch, 1973). However, we go beyond general frameworks by articulating how constructive reactance is dyadically operating in complex and often multiplex systems involved with goals or missions.

Feedback is a critical mechanism for behavioral change, although traditional goal setting and feedback frameworks (Kluger & DeNisi, 1996) have not sufficiently accounted for how this works in the context of social networks involved in targeted goals. Our new conceptualization of feedback linkages (FB) in NGA illustrates how information about the goal pursuit itself is transmitted to various entities across the network, such as through monitoring, observation, and proactive information gathering processes about the goal task itself (Grant & Ashford, 2008). This conceptually utilizes the observing role function in DNT to demonstrate who is getting information or learning about a goal pursuit. Unique to NGA, such information does not need to be interpersonal at all. To illustrate, an employee working alone with complex equipment will often be receiving information, or data, directly from the instruments to create the product. In NGA, this is visualized as a FB link from the goal node back to the employee. However, in other cases, an actor may get feedback about the goal in conjunction with system support from another in the network (S) often in the service of learning and helpful advice functions (Argote & Ingram, 2000). In such a case, the actor is receiving both a FB link from the goal node and an S link from another who is also receiving FB about the actor's goal pursuit and using this information to help and support the actor in the network through the S link.[1] Hence, this process uniquely shows how feedback information and interpersonal connections can work together in

[1] This can also represent sterner cases of advice giving, such as a supervisor who learns about an employee's very poor performance on a goal (i.e., a FB link to supervisor) and then shares the information with the employee (i.e., employee receives a FB link about the goal node as well) while also supporting a change of the ineffective behavior (i.e., a V link to the employee). This illustrates how FB and V linkages can work jointly to explain negative feedback complexities.

complex goal and behavioral pursuit systems. NGA is the first social network approach to advance this conceptual distinction through the use of goal nodes and goal feedback mechanisms.

The final role in DNT is *interacting* (I): actors potentially interacting around those involved in the goal, but are not necessarily helping, hurting, observing, and/or paying attention to those involved. Identifying such entities can be especially important when considering interventions or change, because other actors in the vicinity may transform into motivational roles in a goal pursuit when they receive feedback illustrating that help is needed, for example.

Hypotheses

A rudimentary proposition in DNT is that there should be significant connections between actors in the social network and the target goal nodes, such as through G, P, or and/or FB links (Westaby, 2012). Otherwise, a goal node is not necessary at all to explain complex systems and a traditional social network analysis (SNA) alone is sufficient. When such direct goal node linkages exist, it suggests that independent actions among the entities are engaged in the goal pursuit, such as different actors working on separate tasks alone to achieve a goal. Factory employees working at times on their own clearly illustrates such systems where independence is at play. To test this hypothesis, we will first consider goal striving to be a relational attribute, which "refer to relational phenomena that are not quite social ties but can be treated as such methodologically, and which are seen as both antecedents and consequences of social ties" (Borgatti, Everett, & Freeman¸ 2013, p. 5). Then, we will examine whether there is significant shared independence of goal striving links between actors in the social network.

Hypothesis 1: Goal striving links will be shared among a significant number of entities in the social network.

A second proposition derived from DNT is that if a social network is dependently involved in a target goal pursuit, significant interpersonal connections between the entities should be manifest. In other words, there should be significant, non-zero density among entities in regards to the most relevant roles anticipated in the system (Burt et al., 2013). In the functional goal pursuits examined in this study, we expect that system support (S) links should become activated and thus manifest significant density across the S sub-network, if the network system is interdependently involved. If it is not significant, it suggests that a traditional social network approach is not necessary to explain the given goal pursuit system.

Hypothesis 2: The system support sub-network will manifest significant density.

Taken together, if we find support for both Hypothesis 1 and 2, it suggests what we conceptualize as *multipendence*: A system that has some actions independently involved with the goal and some actions dependently involved. Going beyond independent and interdependent dichotomizations of the self (Markus & Kitayama, 1991), multipendence illustrates that actions in the broader system are not merely independent or dependent, but can be both involved, given that some entities may be independently striving (G), for example, and others are dependently working closely together to help one another (S) achieve a goal.

Lastly, because Westaby (2012) proposed in the original theory that system support often functions in service of goal striving in dynamic network systems, we expect that entities engaged in system support links will also share goal striving links on the goal node. That is, some people will not only work alone on the task (G) during some portions of a goal pursuit, but will also be dependent on others' help and support to achieve the goal during other portions of a goal pursuit (S), especially when challenges are faced, advice is needed, or engaged in tasks that need interpersonal teamwork (Mathieu, Hollenbeck, van Knippenberg, & Ilgen, 2017).

Hypothesis 3: Entities engaged in system support functions will share significant goal striving functions.

Conflict dynamics, which are often at work in many social networks (Park, Mathieu, & Grosser, in press), can inversely explain goal achievement and performance outcomes according to dynamic network theory. In this study, we will assess and explore these dynamics, but not form hypotheses, because of the pro-goal orientation of the goals examined in this study. The hypotheses were tested on two social networks involved in important goal pursuits using different methods. Study 1 used a participant observer ethnography to examine a team's pursuit of its mission. Study 2 used a traditional non-ethnographic approach to study the social network involved in an individual's pursuit of an important task in the person's life. Both studies used network goal surveys from the Dynamic Network Lab, which serves the Columbia University community and partnering researchers and individuals (Dynamic Network Lab, 2019).

Study 1

Participants

We used participant observer ethnography to collect data for a Focal Team and the network involved in its mission. This was deemed a potentially useful initial approach, given both researcher's capacity to be acutely aware of the dynamics associated with this Focal Team while at the same time critically evaluating the network measures in a real-world application with direct experience. This approach is guided by previous scholarship, such as Gioia et al.'s (1994) notion that close connections to a system can provide "direct experience with the knowledge structures…meanings, and perspectives unattainable otherwise", although it can be questioned given that such observation may not be "naïve enough" (p. 367). Guided by this scholarship, we ensured that one of the researchers was blind to the exact hypotheses in this study, when engaging in the survey and discussion process, thereby maintaining a needed "pluralist perspective" and helping mitigate biases associated with a single interpretive perspective from one participant observer, which is "subject to idiosyncrasies" (p. 368). Such an approach also adds rigor over auto-ethnography or self-narratives (Meyer, 2012), which do not allow for comparative challenge to the observed linkages, because of only one observer. This approach also shares similarities with action research in which authors are involved in a given system (Bate, Khan, & Pye, 2000; Sackman, Eggenhofer-Rehart, & Friesl, 2009). Despite some advantages of ethnographic research, because there are clear limitations about such assumptions, designs, and potential bias in data collection (Watson, 2011), we also replicated the analytics from Study 1 in Study 2 using a non-ethnographic sample.

Measures

A three-step survey process was used to assess the social network involved with the Focal Team's mission. Step 1 was entity generation. Step 2 was the quantitative network goal survey. For this, the goal was framed as getting important things done for the Focal Team's mission. This superordinate framing is broad in order to capture the various sub-goals that can exist as well as the numerous day-to-day activities and interactions. Superordinate representation of goals is common in goal pursuit (Austin & Vancouver, 1996).[2] Step 3 was a discussion process.

Step 1: Entity Generation. It was first necessary to derive the entities in the social network involved with the Focal Team's goal. For this, the participant observer researchers responded to items asking who they believed are significantly involved with the Team getting important things done to achieve its mission.

[2] Although it is technically possible to assess and analyze the multiple sub-goals for the Focal Team, it would make an initial survey inordinately lengthy for participants, thus being more applicable for follow-up assessments, if desired in research or practice.

The following instructions were followed:

> Please generate and use names that come most quickly and naturally to mind. Try to keep your list as short and general as possible, yet still covering the main general actors. Try to keep the names as simple as possible using practical language that is commonly used in this setting, such as names that would make sense to others in this system. Include entities that could have negative effects on the mission as well, if they exist. It is ok to initially categorize some entities as questionable or borderline, but then decide not to use them later in your final set, if these entities are already accounted for, or if they are not that significantly involved in the system after further reflection.

The number of entities to generate were not restricted. This helped avoid an issue in traditional social network research where participants are told to indicate an arbitrary number of entities to keep assessments short (e.g., 5), which can lead to a "non-random missing data pattern," such as when only those with many contacts are nominated thus artificially inflating the connectedness of the actors in the network and can result in important entities being omitted, providing an incomplete picture of a complex system (Kossinets, 2006). A limitation of the open-ended approach is that it can result in a longer survey, which can result in fatigue and non-differentiation of the social network role behaviors. However, since we aim to properly assess full systems, we encourage open-ended approaches whenever possible with analysts being committed to the assessments, although more abstracted or broader entity names could be used (e.g., "Friends" instead of individual names for every friend), if time constraints are a serious issue.

In this study, the participant observers created their initial lists separately and then compared results. They were provided the following instructions, when discussing and revising their lists: (1) *If you had slightly different terms to describe the same thing, try to pick one term that is mostly commonly used*, (2) *use broader names when it appropriately helps simplify the system*, and (3) *keep names as brief as possible, since it is easier to visualize in the follow-up survey and computer graphics*. Overall average agreement was 86.5% on the initial lists and remaining discrepancies were resolved through discussion. The following nine entities were indicated as having important motivational involvement in the system: Focal Team, Unit 2, Unit 1, Competition, Technology (Tech.) Units, Funding Sources, External (Ext.) Collaborators, Online Resources. Names were modified or changed for confidentiality.

Step 2: Network Goal Survey. Approximately two weeks after the entity generation assessment, participant observers independently completed the network goal survey. All of the social network role assessments in the survey pivoted around the Focal Team's goal node. The goal node and the list of entities were piped throughout an online survey using Qualtrics software. All inter-combinations of entities, dependent social network roles (S, V, N, and R) and independent roles with the goal node (G, FB, and P) were assessed, thereby allowing relevant adjacency matrices to be generated.[3] Subjective confidence ratings were also assessed on a 11-point scale from 0% to 100% in 10% increments on all of the social network role measures. Confidence was consistently rated between 70% and 90% on all ratings by both participant observers. The specific items for each social network role are shown below with initial agreement between participant observers indicated in parentheses. Again, the Focal Team goal node was framed in the survey as "Getting important things done for the Team's Mission": Goal Striving: *How often are the entities below independently working on the Team's goal, such as on their own or by themselves?* (100%). System Supporting: *How often do/does "X" help or support each of the following entities in order for the Focal Team to achieve its goal?* (95.83%). Feedback: *How often does each of the following entities get feedback about the Focal Team's goal?* (88.89%). Goal Prevention: *How often do the following entities independently do things that can obstruct the Focal Team's goal?* (88.89%). Supportive Resisting: *How often do/does*

[3] When all network actors can participate in the survey, each actor only needs to respond to her/his own inbound and outbound role linkages and then the individual surveys can be combined via computer to represent the entire network, thereby shortening each individual survey. However, this requires that every network actor participate in the survey, which is often difficult in large systems; hence using knowledgeable representatives can be helpful.

"X" engage with the entities below which can obstruct the Focal Team's goal? (100%). System Negating: *How often do/does "X" get upset with the following entities in relation to the Focal Team's goal?* (100%). System Reacting: *If "X" gets into a conflict with any of the entities below in relation to the Focal Team's goal, how often do/does "X" react constructively to each entity below?* (100%). Each item was scored [and visualized in chart form] on a four-point scale ranging from *not often (or not relevant)* = 0 [no line in the graphs], *sometimes* = 1 [thin line], *often* = 2 [medium line], and 3 = *extremely often* [thick line].[4]

Step 3: Discussion Process. After the surveys were completed independently, the participant observers joined again to share their survey responses, alternating who shared their answers first for each page in the survey in a counter-balanced fashion. The other participant observer would then indicate agreement or disagreement on the items and ask clarification questions as needed to understand the other's ratings on each page. In cases of disagreement or lack of information, the participant observers could provide examples to justify the existence of a rating (e.g., X supported Y's goal because X gave some funding to Y last month). The agreed upon response was then entered into another final Qualtrics network goal survey to capture the system dynamics. If a disagreement remained, "Don't Know" was entered into the online survey to capture these responses, which technically indicates that a link would not be shown or calculated in the network visualizations and analytics. The method of not displaying linkages in network assessments when there is lack of agreement is consistent with past approaches for social network analysis (Kilduff, Crossland, Tsai, & Krackhardt, 2008). More broadly, such a discussion process is helpful in more rigorous participant observer ethnographic research,

[4] In subsequent studies, we find that a 3-point scale, eliminating "extremely often" helps ease the discussion process in Step 3, while the 4-point scale is useful for individual network assessments when a discussion process is not used, such as our approach in Study 2. For the *system reacting* item, an option of "There is no conflict" was also provided, which, if selected, was scored 0 as well for the scale.

because it allows for perceptions to be compared and challenged, which is otherwise not possible when single ethnographers engage in research (Leigh et al., 2006). This is consistent Gioia et al.'s (1994) perspective that: "The heart of the initial stage of the grounded approach is the method of constant comparison" (p. 368).

Results

Results from the Qualtrics-based network goal survey were transformed into visuals using R programming and network packages (R Core Team, 2017), in accord with DNT parameters. Hypotheses were analyzed using UCInet software (Borgatti, Everett, & Freeman, 2002). In network goal analysis, the goal can be visually displayed with ovals and entities with squares. Social networks roles are displayed on the manifest links as G, S, FB, P, V, N, and/or R.

Functional Relations

The goal striving sub-network and link intensities are shown in Part A of Figure 1. The thicker the line, the stronger the goal striving (G), consistent with the 4-point scale used in the network goal survey. In this case, the Focal Team, Unit 1, Unit 2, and Ext. Collaborators are each independently goal striving for the Team's mission, with the Focal Team manifesting the strongest connection to the goal, as one would expect.

There are important issues to consider when testing social network systems, given the dependencies involved (Snijders, 2011). To test hypotheses, we used non-parametric statistical tests and QAP correlation (Cranmer et al., 2016; Krackhardt, 1987) to determine if there were G and S relations between actors in the network (or if the proportion / density of G and S relations are significantly different from zero) as examined in the first two hypotheses. We also used this approach to test the last hypothesis, which examines whether entities engaging in S functions share significant G functions.

To test Hypothesis 1, which examines if there is a significant amount of G in the network, we first converted the two-mode network data which links the two types of nodes collected in the survey (i.e., social network entities and goal node), into a one-mode, actor-by-actor matrix using the row projection technique (Everett & Borgatti, 2013; Grassi, Calderoni, Bianchi, & Torriero, 2019). The result of the data transformation is a goal striving adjacency matrix in which the (i, j) cell is the extent to which actors i and j share independent goal striving functions, and 0 if at least one actor i or j is not striving for the goal. Results provided support for the hypothesis revealing that the observed density of the goal striving network (.17) is significant ($Z = 2.55$, $p < .05$), or that a significant proportion of entities in the network are independently goal striving.

The system support (S) sub-network and centrality indicators are shown in Part B of Figure 1. This analysis is akin to traditional social network analysis when goals are not included; in this analysis, centrality is a powerful statistic to infer actor importance (Balkundi, Kilduff, & Harrison, 2011). Descriptive results indicated that Unit 2 and the Focal Team are supporting each other, as well as the Ext. Collaborators, in pursuing the Team's mission. The Focal Team is most central in the system among the entities themselves. Hypothesis 2 examines if a significant proportion of actors are supporting others in the network. As predicted, we found the observed density of the S network (.24) to differ significantly from zero ($Z = 2.47$, $p < .05$), indicating that there is a significant proportion of entities in the network that are providing support to others.

The network motivation sub-network is shown in Part C of Figure 1. This network includes the goal node and shows both G and S role activations. This visualizes how the entities in the network are working independently and/or dependently toward the goal. Examining network motivation in a system is further validated if there are shared G and S linkages among the entities, consistent with Hypothesis 3. We used QAP correlation (Krackhardt, 1987) to test the hypothesis that those supporting each other tend to share independent goal striving functions with others in the network. As predicted, the correlation between system support and goal striving functions was significant ($r = .55$, $p < .05$), suggesting that system support and goal striving functions are positively related in the context of this goal pursuit.[5] All relations among theoretical variables are shown in Table 1. Given that the relations between the other variables in DNT were not inordinately high, it demonstrates rudimentary construct validity among DNT constructs, although future confirmatory factor analytics are necessary.

Finally, descriptive results indicate that the Focal Team's mission goal node also had high levels of betweenness centrality (16.5), which is a critical metric to describe entities that are connecting elements across the full system (Burt et al., 2013).[6] In this case, it statistically confirms that the goal node is indeed uniquely connecting the system together such as through G, P, or FB functions involved in the goal pursuit.

Full System

Negative relationships and conflict are common in many network systems (Labianca & Brass, 2006). DNT delineates what are theoretically presumed to be the most important conflict relations involved in human goal pursuit: Independent goal prevention (P), supportive resistance (V), system negation (N), and constructive system reactance – serving as a potential cooperative force in the face of experienced conflict (R). The full network goal system was explored, which includes these linkages as shown in Part A of Figure 2. Here, we can see that the Focal Team

[5] Autocorrelation should be accounted for in network analyses (Dekker, Krackhardt, & Snijders, 2007). QAP correlation accounts for the interdependencies among the dyadic relations between the actors in the network (or autocorrelation) by preserving the nature of those dependencies in the analysis. This is done by permuting the rows and columns of the observed matrices, and comparing the distribution of correlations of the permuted matrices with the observed correlation between the matrices (Borgatti, Everett, & Johnson, 2013; Cranmer et al., 2016). We used 50,000 permutations for these tests in order to stabilize the p-values, in line with previous publications.

[6] Betweenness indicates the prominence of an entity by summing the number of times other entities need go through that entity to reach another entity in the network along the shortest path (Freeman, 1978/79).

itself plays a role in the direct obstruction of its own work, such as falling behind schedule on needed tasks. Betweenness indicators also demonstrate that the Focal Team maintains a high level of centrality across the full system. By including all motivational roles in the system, we now see that the External Collaborators are relatively more central in the system as compared to what was learned about their centrality from only system support. This means that this entity was involved in both complex positive and negative forces in the system. The full analysis also demonstrates the importance of including the conflict roles in DNT to accurately capture who is involved in complex systems.

We also calculated overall summaries to describe full system dynamics. Fortunately, DNT provides guidance on how to combine the social network role data into meaningful summaries at the macro, system level. Results indicated that the system had a high *positive system focus*: 81%. This represents the percentage of role links dealing only with purely positive motives (G and S divided by G, S, P, V, N, and R, not including peripheral roles). The *network affirmation ratio* was even more positive: 88%. This represents the percentage of functional efforts to manage the network goal system, including constructive efforts to deal with conflict (i.e., G, S, and R divided by G, S, P, V, N, and R, not including peripheral roles). These results also correspond to both participant observers strongly agreeing to 5-point Likert items asking if the Focal Team's goal has made a lot of progress, been on track with the plan, and been achieved.

Study 2

Although participant observer ethnographies have some benefits, they also have a number of limitations (Watson, 2011). Hence, a second study was conducted using the same measures reported above but in a non-ethnographic design examining an individual's important self-selected goal pursuit. In this case, the goal was to accomplish current projects. This data was collected in the context of a graduate level course in which participants were pursuing an important and real goal in their life space and trying to intervene to accomplish it over several months. In this replication study, the participant doing the system self-assessment was female, between 20 to 30 years of age, and employed.

Study 2 used the same survey process as Study 1, but the participant completed it individually without a discussion with other network members. The participant was also encouraged to take breaks as needed, when feeling fatigued, given survey length. The data was analyzed in the same manner as Study 1 to test key hypotheses. Results replicated Study 1 and key propositions in DNT. In support of Hypothesis 1, there were significant shared connections of goal striving with the goal node ($Z = 3.02$, $p < .01$). Hypothesis 2 confirmed significant system support density ($Z = 2.62$, $p < .01$). Hypothesis 3 was supported by finding that the reported entities engaged in the S network shared significant levels of G linkages ($r = .77$, $p < .01$). As further support for DNT and the power of NGA, we also found that the goal node manifested substantive betweenness centrality, indicating that the goal node was again connecting entities across the network, especially through FB links. Lastly, supplemental analyses indicate that the conflict subnetwork (P, V, N, and R) revealed significant density ($Z = 2.42$, $p < .05$).

Discussion

The purpose of this study was to advance our NGA framework to examine fundamental concepts from dynamic network theory. A participant observer ethnographic design was used in Study 1, and a traditional non-ethnographic design was used in Study 2. Results from both studies indicated that independent goal striving was shared in the systems. This means that a significant number of entities in the network were independently working alone or by themselves on the goals or missions. This illustrates the importance of including goal nodes in network analytics because it allows us to visualize the critical goal striving and feedback linkages involved in dynamic systems. Second, system support was significantly manifest across the networks to achieve goals. That is, some entities were dependently helping and supporting each other in the goal pursuit process, indicating the power of social network linkages involved in human action, consistent with traditional SNA. Third, both studies showed that those engaged in goal striving were also more likely to share system support functions with others in their networks. This indicates that some people may also be switching between working independently or alone on tasks and then working dependently with others in a network to attain goals.

Taken together, NGA showed how entities in the network were working together and/or separately on goals in what we refer to as multipendent systems. Multipendence occurs in systems when some entities work independently on needed tasks, some dependently, and some may switch back and forth between independent and dependent tasks. This concept goes beyond the independent / interdependent conceptualization of self (Markus & Kitayama, 1991) by illustrating that more complex systems can be multiply determined by both the independence and dependence of the actions of various networked entities. Multipendence does not occur when people are either working entirely together or entirely separately in a system.

Other results demonstrated that the goal node was structurally important, given that the goal node revealed high levels of betweenness centrality in both networks. This also illustrates that the goal was uniquely connecting the system together, such as through direct feedback from the goal pursuit, which was not fully explained through social connections alone. For example, entities were likely learning about their goal progress directly from the task at hand without it necessarily being connected to support or resistance functions from others. The goal node thus serves as a direct broker of information about success or failure when working on a task. In other cases, it may work in tandem with system support linkages from others, such as a supervisor receiving feedback about a subordinate's goal pursuit first and then chatting with the subordinate about it as a system supporter to help increase the likelihood of achievement.

Broadly speaking, without NGA, the centrality of goals in structuring human relationships would have been more hidden from our understanding. By visualizing linkages from dynamic network theory through NGA, we were aiming to make "invisible work visible" in line with artful descriptions by Cross, Borgatti, and Parker (2002, p. 25). Our work contributes to this important perspective by incorporating goal striving, preventing, and feedback functions around goal nodes to further explain complex social and organizational behavior. These can serve important independent functions that can drive success or failure in human systems. This also contributes to the traditional goal setting, control theory, and feedback literatues in psychology and management (Kluger & DeNisi, 1996; Locke & Latham, 2002) by showing how feedback functions in the context of other important social network roles such as system support (to continue trajectories) or supportive resistance (to change trajectories).

Analytics and Interventions

Given our use of computer analytics, a practical advantage of NGA of complex systems is that it allows researchers and practitioners the technological ability to effortlessly zoom-in on different positive and/or inhibitive social forces involved in a system (e.g., Figure 1 and 2). By clicking through the different motivational sub-networks, one can visualize rather quickly how well a system is functioning positively (blue) or with conflict (red hues), generally speaking. These visuals also mesh with the overall metrics and ratios provided by our NGA framework as well, such as the positive focus ratio. These statistical summaries are particularly helpful when the systems are very large and densely populated with network linkages, making full system visualization more difficult. Researchers or practitioners can also zoom-in effortlessly on each individual entity's behavior in the system to aid understanding. Additional metrics about individual behavior can be gleaned as well, beyond the centrality indicators already demonstrated in the figures. For example, one can calculate an entity's ratio of G, S, P, V, N, and R. To illustrate, in Part B of Figure 2, we see that Unit 1 manifests non-zero outdegree ratios for G, S, N and R. Additional metrics of individual complexity are also possible. We illustrate three new concepts in network goal analyses in terms of outdegree links. First, researchers can assess *individual volume* (iv), representing how many people or goals an individual entity is connected to directly through any type of motivational role, positive or negative.[7] This is simply the number of other entities or goals an entity is connected to in any way. For example, in Figure 2, we see that Unit 1 is linked to two recipient nodes: Focal Team (by one multiplex arc of S, N, and R) and the Team's Mission goal node (G). Individual volume ratio divides the volume of these recipients by the total number of possible recipients, including the goal node(s). Second, one can examine *individual multiplexity* (*im*) which represents how many different types of social network roles a social entity simultaneously displays to others in the network as parameterized through DNT. For example, a person that only shows system support to other people (no matter how many) has low individual multiplexity (1), while another person showing a rich display of S, V, N and R linkages to only one person would have higher individual multiplexity (4). In ratio form, this captures the percentage of all possible multiplex links between an entity and other social or goal nodes in the full system (e.g., 0 means an isolate with

[7] Where 0 indicates no link and 1 indicates that any type of link is manifest dyadically.

no links with others of any kind, while 1.0 indicates that an entity is displaying every kind of social network role among the manifest connections).[8] Combining these two factors together can also illustrate an individual's *individual complexity* (*ic*): How much an individual entity is connected to various people and goals in diverse and multiplex ways. This can be statistically represented with different functions, such as summative ($ic = iv + im$) or multiplicative forms ($ic = iv * im$). For example, Unit 1 has an outdegree multiplicative complexity ratio of .14.

Given analytic insights generated from NGA, it sets the stage to plan network goal interventions. These interventions typically represent the manipulation of goals, network roles, and system processes aimed to generate positive system functioning or emergent outcomes, such as performance, climates, or system well-being. In application, practitioners would first *brainstorm* interventions informed by the NGA results of their investigation. Table 2 illustrates various strategies change agents can consider when brainstorming about their systems. Once a set of ideas are brainstormed, the most important and realistic tactics should be prioritized since it is often impractical to immediately implement all possible interventions. To illustrate one important tactic, based on DNT, it is often critical to build network motivation around the goal by adding, or strengthening existing, G and S links in the system. This means getting more people to work on the goal directly as well as support one another as needed. It can also be helpful to mitigate dysfunctional conflict forces, such as P, V, and N links, when possible. See network goal interventions at DynamicNetworkLab.Org for more details about intervention tactics. Second, a clear *plan* should be finalized. During this process, it is important to be mindful of potential deadlines, needed budgets, sub-goal routines, and potential contingency plans, if obstacles are confronted. As many leaders and change agents know, interventions and

[8] In the simplest parameterizations of DNT, the max possible motivational multiplex links to each social entity is 4 (i.e., S, V, N, and R) and to goals is 2 (i.e., G and P).

behavioral change is often nonlinear and planning for set-backs, unintended consequences, and alterative pathways in advance can help result in positive change, consistent with if/then thinking in social psychology (Gollwitzer, 1999). Finally, entities in the system need to *implement* the plan and gather feedback over time to make further modifications as needed.

In all, the above approach has been used in our practice to help numerous people achieve their goals, ranging from getting jobs and completing organizational projects to quitting smoking and losing weight (Westaby et al., 2014). Moreover, in the current research, the participants in both Study 1 and Study 2 indicated significant progress in goal achievement.

Limitations and Future Research

There were several limitations in this study. First, only two networks were examined. One network was based on a participant observer ethnographic method, which can have bias. In response, Study 2 replicated Study 1 using a non-ethnographic design. While examining such individual networks is common in the social network literature, more research is needed testing multiple networks using multilevel analyses (Brass, Galaskiewicz, Greve, & Tsai, 2004). Second, longitudinal data was not examined in this study, nor was experimental manipulation possible. Thus, we cannot infer causal influence. Future research needs to start isolating causal mechanisms, especially in the context of interventions over time. Third, we were unable to gather data from all entities in these systems, but did ask the participants to generate their ratings of all relations in the system, thus providing a full perceptive view. Although leaders and change agents often need to base their important decisions on exactly such perceived dynamics, assessing more entities in the network and comparing their perceptions can help assess dynamic network intelligence, according to dynamic network theory: How accurate entities are at reading others' motives and relations in goal pursuit systems. A fruitful extension would be incorporate cognitive social structures (Kilduff et al., 2008) and transactive memory processes (Ren, Carley, & Argote, 2006) in NGA.

NGA will need to be compared to other analytic approaches, such as stakeholder analysis, causal loop modeling, and accountability mapping models. Studies articulating when and where different analytics are helpful for different types of intervention planning will be helpful in the organizational change literature as well. More work is also needed to understand complex feedback dynamics, particularly how outcomes of goal pursuits, such as successes and failures, resonate with goal strivers and system supporters and influence change mechanisms in the network. Likewise, integrative frameworks in the context of NGA should examine knowledge transfer (Argote & Ingram, 2000), network contagion (Christakis & Fowler, 2007), social interaction analysis (Westaby, Woods, & Pfaff, 2016), performance analysis systems (Soltis, Brass, & Lepak, 2018), network change (Hollway, Lomi, Palloti, & Stadtfeld, 2017), and system dynamics (Snijders, van de Bunt, Gerhard, & Steglich, 2010).

Lastly, confidentiality, data privacy/security, and ethics need to be of utmost importance whenever doing NGA, given that highly sensitive data is collected about perceived entities and their behavior, including potential conflict. In our research we use multiple layers of data masking to protect confidentialities in assessed systems. For example, participants do not use last names in the survey and can also use aliases or generic codes for other entities represented in their systems, so true identities can be refracted.[9]

[9] When participants use aliases, generic codes, or false/masked names, they are reminded to write down the true names for such codes in another safe location so that they can interpret their computerized visualized feedback reports provided by our lab for their personal learning, education, and intervention planning, if desired. Moreover, participants' real names are not shown in computerized feedback reports. Instead, a term such as "Focal Entity" could be used, which the participants would understand is them in the visuals.

In all, this study contributed to the literature by using NGA to understand complex systems. Grounded in dynamic network theory, we used advanced technologies to visualize the network environments (Leonardi, 2013). Such analytics and conceptual grounding helped provide new insights into planning interventions in the context of social networks (Stadtfeld et al., 2016). Given clear operationalizations in NGA, this study also helped alleviate ambiguities that are sometimes found in more general explanations of complex networks (Srivastava, 2015). Future research is needed to further test and apply NGA in different social, organizational, online, and international domains.

References

Argote, L, & Ingram, P. (2000). Knowledge transfer: A basis for competitive advantage in firms. *Organizational Behavior and Human Decision Processes, 82,* 140-169.

Austin, J. T., & Vancouver, J. B. (1996). Goal constructs in psychology: Structure, process, and content. *Psychological Bulletin, 120*, 338-375.

Balkundi, P., Kilduff, M., & Harrison, D. A. (2011). Centrality and charisma: Comparing how leader networks and attributions affect team performance. *Journal of Applied Psychology*, 96, 1209–1222.

Bate, P., Khan, R., & Pye, A. (2000). Towards a culturally sensitive approach to organization structuring: Where organization design meets organization development. *Organization Science, 11,* 197-211.

Brass, D. J., Galaskiewicz, J., Greve, H. R., & Tsai, W. (2004). Taking stock of networks and organizations: A multilevel perspective. *Academy of Management Journal*, 47, 795–817.

Battilana, J. & Casciaro, T. (2012). Change agents, networks, and institutions: A contingency theory of organizational change. *Academy of Management Journal, 55,* 381-398.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science*, 323, 892–895.

Borgatti, S. P., Everett, M.G., & Freeman, L.C. (2002). Ucinet for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies.

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (*2013*). *Analyzing Social Networks*. Thousand Oaks, CA: Sage.

Borgida, E., Sullivan, J. L., Oxendine, A., Jackson, M. S., Riedel, E., & Gangl, A. (2002). Civic culture meets the digital divide: The role of community electronic networks. *Journal of*

Social Issues, 58, 125-141.

Bovasso, G. (1992). A structural analysis of the formation of a network organization. *Group and Organization Management, 17,* 86-106.

Burke, W. W. (2014). Changing loosely coupled systems. *Journal of Applied Behavioral Science, 50,* 423-444.

Burt, R. S., Kilduff, M., & Tasselli, S. (2013). Social network analysis: Foundations and frontiers on advantage. *Annual Review of Psychology, 64*, 527–547.

Christakis, N. A. & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine, 357,* 370-379.

Cranmer, S. J., Leifeld, P., McClurg, S. D., & Rolfe, M. (2017). Navigating the range of statistical tools for inferential network analysis. *American Journal of Political Science, 61,* 237-251.

Contractor, N. S., Wasserman, S., Faust, K. (2006). Testing multitheoretical, multilevel hypotheses about organizational networks: An analytic framework and empirical example. *Academy of Management Review, 31,* 681-703.

Cross, R., Ernst, C., & Pasmore, B. (2013). A bridge too far? How boundary spanning networks drive organizational change and effectiveness. *Organizational Dynamics, 42,* 81-91.

Cross, R., Borgatti, S. P., & Parker, A. (2002). Making invisible work visible: Using social network analysis to support strategic collaboration. *California Management Review, 44,* 25-46.

De Cremer, D., & Tyler, T. R. (2005). Managing group behavior: The interplay between procedural justice, sense of self, and cooperation. *Advances in Experimental Social Psychology, 37,* 151-218.

Dekker, D., Krackhardt, D., & Snijders, T.A.B. (2007) Sensitivity of MRQAP Tests to Collinearity and Autocorrelation Conditions. *Psychometrika, 72,* 563-581

Deutsch, M. (1973). *The resolution of conflict: Constructive and destructive processes*. New Haven, CT: Yale University Press.

Dynamic Network Lab (2019). Retrieved from www.DynamicNetworkLab.Org.

Everett, M. G. & Borgatti, S. P. (2013). The dual projection approach for two mode networks. *Social Networks, 35*, 204-210.

Freeman, L. C. (1979). Centrality in social networks conceptual clarification. *Social Networks, 1,* 215-239.

Gioia, D. A., Thomas, J. B., Clark, S. M., & Chittipeddi, K. (1994). Symbolism and strategic change in academia: The dynamics of sensemaking and influence. *Organization Science, 5*, 363-383.

Gollwitzer, P. M. (1999). Implementation intentions: Strong effects of simple plans. *American Psychologist*, *54*, 493–503.

Grant, A. M., & Ashford, S. J. (2008). The dynamics of proactivity at work. *Research in Organizational Behavior*, *28*, 3-34.

Grassi, R., Calderoni, F., Bianchi, M., & Torriero, A. (2019). Betweenness to assess leaders in criminal networks: New evidence using the dual projection method. *Social Networks, 56,* 23-32.

Hollway, J., Lomi, A., Palloti, F., & Stadtfeld, C. (2017). Multilevel social spaces: The network dynamics of organizational fields. *Network Science, 5,* 187-212.

Kilduff, M., Crossland, C., Tsai, W., & Krackhardt, D. (2008). Organizational network perceptions versus reality: A small world after all? *Organizational Behavior and Human*

Decision Processes, *107*, 15-28.

Ingram, P. & Yue, L. Q. (2008). Structure, affect and identity as bases of organizational competition and cooperation. *The Academy of Management Annals, 2,* 275-303.

Kilduff, M., & Tsai, W. (2003). *Social networks and organizations.* London, England: Sage.

Kluger, A. N., & DeNisi, A. (1996). Effects of feedback intervention on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin, 119*, 254-284.

Kossinets, G. (2006). Effects of missing data in social networks. *Social Networks, 28*, 247-268.

Kozlowski, S. W. J., Watola, D., Jensen, J. M., Kim, B., & Botero, I. (2009). *Developing adaptive teams: A theory of dynamic team leadership*. In E. Salas, G. F. Goodwin, & C. S. Burke (Eds.), Team effectiveness in complex organizations: Cross-disciplinary perspectives and approaches (pp. 113-155). New York, NY: Routledge Academic.

Krackhardt, D. (1987). QAP partialling as a test of spuriousness. *Social Networks, 9,* 171-186.

Labianca, G., & Brass, D. J. (2006). Exploring the social ledger: Negative relationships and negative asymmetry in social networks in organizations. *Academy of Management Review*, *31*, 596 – 614.

Lazer, D. Pentland, A. Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D., & Van Alstyne, M. (2009). Computational social science. *Science, 323,* 721-723.

Leigh, T.W., Peters, C., & Shelton, J. (2006). The consumer quest for authenticity: The multiplicity of meanings within the MG subculture of consumption. *Journal of the Academy of Marketing Science, 34,* 481-493.

Leonardi, P. M. (2013). When does technology use enable network change in organizations? A comparative study of feature use and shared affordances. *MIS Quarterly, 37,* 749-775.

Levine, J. M., & Kerr, N. L. (2007). Inclusion and exclusion: Implications for group processes. In A. E. Kruglanski & E. T. Higgins (Eds.), *Social psychology: Handbook of basic principles* (2nd ed., pp. 759-784). New York: Guilford.

Lewin, K., & Cartwright, D. (1951). *Field theory in social science*. New York: Harper & Brothers.

Locke, E.A., & Latham, G.P. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American Psychologist, 57*, 705-717.

Macri, D. M., Tagliaventi, M. R., & Bertolotti, F. (2002). A grounded theory for resistance to change in a small organization. *Journal of Organizational Change Management, 15,* 292-310.

Markus, H. R. & Kitayama, S. (1991). Culture and the self: Implications for cognition, emotion, and motivation. *Psychological Review, 98,* 224-253.

Meyer, C. B. (2012). When radical reforms are on the agenda: Managing politics in Government. *The Journal of Applied Behavioral Science, 48,* 194–224.

Newman, M. E. J. (2003). The structure and function of complex networks. *SIAM Review, 45,* 167-256.

Mathieu, J. E., Hollenbeck, J. R., van Knippenberg, D., & Ilgen, D. R. (2017). A century of work teams in the Journal of Applied Psychology. *Journal of Applied Psychology, 102,* 452-467.

Park, S., Mathieu, J. E., & Grosser, T. J. (in press). A network conceptualization of team conflict. *Academy of Management Review.*

Pickering, J. M. & King, J. L. (1995). Hardwiring weak ties – interorganizational computermediated communication, occupational communities, and organizational change. *Organization Science, 6,* 479-486.

Ren, Y. Q., Carley, K. M., & Argote, L. (2006). The contingent effects of transactive memory: When is it more beneficial to know what others know? *Management Science, 5,* 671-682.

Rhoades, L., & Eisenberger, R. (2002). Perceived organizational support: A review of the literature. *Journal of Applied Psychology, 87*, 698-714.

Sackman, S. A., Eggenhofer-Rehart, P. M., & Friesl, M. (2009). Sustainable change: Long-term efforts toward developing a learning organization. *The Journal of Applied Behavioral Science*, *45*, 521–549.

Shah, J. Y., & Kruglanski, A. W. (2008). Structural dynamics: The challenge of change in goal systems. In J. Y. Shah & W. L. Gardner (Eds.), *Handbook of motivation science* (pp. 217-229). New York: The Guilford Press.

Snijders, T. A. B. (2011). Statistical models for social networks. *Annual Review of Sociology, 37,* 131-153.

Snijders, T. A. B., van de Bunt, G. G., Gerhard, & Steglich, C. E. G. (2010). Introduction to stochastic actor-based models for network dynamics. *Social Networks, 32,* 44-60.

Soltis, S. M., Brass, D. J., & Lepak, D. P. (2018). Social resource management: Integrating social network theory and human resource management. *Academy of Management Annals, 12, 537-573.*

Stadtfeld, C., Mascia, D., Palloti, F., & Lomi, A. (2016). Assimilation and differentiation: A multilevel perspective on organizational and network change. *Social Networks, 44,* 363-374.

Srivastava, S. B. (2015). Intraorganizational network dynamics in times of ambiguity.

Organization Science, 26, 1365-1380.

Tetlock, P. E. (2010). Second thoughts about expert political judgment: Reply to the symposium. *Critical Review, 22,* 467-488.

Watson, T. J. (2011). Ethnography, reality, and truth: The vital need for studies of 'How things work' in organizations and management. *Journal of Management Studies, 48,* 202-217.

Watts, D. J. (2004). The "new" science of networks. *Annual Review of Sociology, 30,* 243–270.

Westaby, J. D. (2012). *Dynamic network theory: How social networks influence goal pursuit.* Washington, DC: American Psychological Association.

Westaby, J. D. (2005). Behavioral reasoning theory: Identifying new linkages underlying intentions and behavior. *Organizational Behavior and Human Decision Processes, 98,* 97-120.

Westaby, J. D., Pfaff, D. L., & Redding, N. (2014). Psychology and social networks: A dynamic network theory perspective. *American Psychologist, 69,* 269-284.

Westaby, J. D. Probst, T. M., & Lee, B.C. (2010). Leadership decision-making: A behavioral reasoning theory analysis. *Leadership Quarterly, 21,* 481-495.

Westaby, J. D., & Shon, D. (2017). Simulating the social networks in human goal striving. In R. R. Vallacher, S. J., Read, & A. Nowak (Eds.), *Computational models in social psychology* (1st ed.). pp. 231-257. New York, NY: Psychology Press.

Westaby, J. D., Woods, N., & Pfaff, D. L. (2016). Extending Dynamic network theory to group and social interaction analysis: Uncovering key behavioral elements, cycles, and emergent states. *Organizational Psychology Review, 6, 34-62.*

Table 1. Correlations and Descriptive Statistics among Dynamic Network Theory Variables

	G	S	FB	P	V	N	R
(a) Study 1: Team Mission							
Goal striving (G)	---						
System supporting (S)	.44*	---					
Feedback (FB)	.31	.48*	---				
Goal preventing (P)	-.08	.00	-.09	---			
Supportive resisting (V)	.15	.25	.44*	.00	---		
System negating (N)	.27	.18	-.06	.00	-.02	---	
System reacting (R)	.34	.37*	.11	.00	.16	.27	---
Mean	.33	.26	.50	.22	.03	.01	.25
SD	.85	.50	.92	.42	.16	.18	.77
(b) Study 2: Accomplish Projects							
Goal striving (G)	---						
System supporting (S)	.77**	---					
Feedback (FB)	.68	.56	---				
Goal preventing (P)	-.39	-.32	-.27	---			
Supportive resisting (V)	.04	.26	.21	-.08	---		
System negating (N)	-.02	.18	.22	-.13	.48	---	
System reacting (R)	.51	.50	.34	-.29	.58	.23	---
Mean	1.33	.90	1.50	.50	.23	.07	.60
SD	.94	1.14	.50	.50	.42	.25	1.05

* = $p < 0.05$, ** = $p < 0.01$

Table 2. Potential Strategies When Generating Network Goal Interventions

Strategy 1: Additions	
A. Network motivation	Adding new goal strivers and system supporters can build powerful interventions (Westaby et al., 2014). Or, the current actors in the network can increase their levels of goal striving (G) or system supporting (S) to bolster achievement. Effective leadership can help orchestrate such transformations.
B. Strong goals	Goals that are compelling, meaningful, important, inspiring, specific, and challenging (Locke & Latham, 2002; Shah & Kruglanski, 2008) can trigger and maintain G and S (Westaby, 2012). Sub-goal routines and operations should be efficient to maximize performance outcomes.
C. Feedback linkages	Improving feedback linkages can aid goal pursuit (Kluger & DeNisi, 1996) by providing goal strivers and system supporters with crucial information to make modifications.
D. System competency	Bolstering system competency can facilitate achievement (Westaby, 2012), such as through self-learning, continuing education, formal training, or the use of new technologies. Creating connections with skilled actors is often key, such as with skilled leaders, experts, advisers, consultants, coaches, mentors, or counselors.
E. Constructive reactance	Using constructive reactance (R) when confronting heated conflict (N) can help mitigate hostilities and reduce escalation (Westaby, et al., 2016). Leadership that encourages active listening, compassion, and empathy among network entities are strategies to help re-stabilize systems (Cross, Ernst, & Pasmore, 2013).
F. Participative decision making	Promoting participation in decision making can help secure system support in groups and complex systems (Kozlowski et al., 2009). This helps provide justifiable reasons and explanation (Westaby, 2005), which can promote feelings of procedural justice in human systems and mitigate conflict (De Cremer & Tyler, 2005).
Strategy 2: Reductions	
A. Network resistance	Reducing or eliminating dysfunctional resistance linkages (P and V) can increase achievement possibilities (Westaby, 2012). Reducing resources or enacting sanctions to mitigate such resistance is one example (Macri, Tagliaventi, & Bertolotti, 2002)
B. Dysfunctional negation	If unhealthy system negation occurs (N), training, education, coaching, or counseling for initiators may help attenuate instances. Anger management training or exclusion may be needed in more extreme cases.
C. Network inefficiencies	Mitigating network inefficiencies can facilitate achievement, such as attending to bottlenecks, missing linkages, or poor workflow (Kilduff & Tsai, 2003). Creating S linkages to those with high system competence can help.
D. Caution if exclusion	Negative psychological outcomes can occur when people feel excluded (Levine & Kerr, 2007), so care should be taken if interventions exclude others.
E. Unintended consequences	Change in one system can inadvertently change other systems. Be mindful of the whole system or gestalt of inter-related systems, while also recognizing that predicting system outcomes is not easy (Tetlock, 2010).
Strategy 3: Dynamics	
A. Centrality and leadership	Promoting the efficient flow of information, operations, or resources, especially through G and S linkages over time can further aid goal pursuits. Thus, entities in (needed) central positions, such as leaders or brokers, are often instrumental in managing these processes (Balkundi et al., 2011; Borgatti et al., 2009; Burt et al., 2013).
B. Interactions	Being in the presence of others with similar goals can (re)trigger or increase motivation, such as through implicit processes (Gollwitzer & Bargh, 2005), especially if intrinsic interest in G and S wanes.
C. Subgroup dynamics	When a network expands in pursuit of goals, clarifying group structures can promote cohesion (Kozlowski et al., 2009). However, it is important to try to inhibit dysfunctional ingroup/outgroup biases if they emerge.
D. Progress	Making progress, even small steps, can be critical to maintain network motivation, which, in turn, can result in achievement over time through G and S. This can reduce procrastination, a common obstacle in human pursuits.
E. Network rippling of emotions	Celebrating progress or success can bolster network motivation through the network rippling of emotions (Westaby, 2012). However, potential envy dynamics can ironically thwart such activities for some actors in the network. Leaders should be mindful of full system dynamics as well as interactions among the sub-networks.
Strategy 4: Analysis	
A. Analytics	Performing network goal analyses (NGA) to understand and track changes over time can promote accountability and identify further modifications. Soliciting advice from skilled leaders or experts in NGA may help generate additional transformations, especially when the actors embedded in the system are lacking new strategy.
B. Decision-making	When important decisions are needed, engaging in thorough decision-making processes may increase confidence or accuracy. The *decision arguments* approach in behavioral reasoning theory may be helpful as one framework (Westaby et al., 2010). This goes beyond pros and cons, by incorporating counter arguments based on reasons.
C. Dynamic network intelligence	Having dynamic network intelligence (Westaby et al., 2014) about reactions to potential interventions may result in greater acceptance to change, such as refraining from strategies that could create dysfunctional negation links (N) among important actors in the network motivation roles of G and S.
D. System aware, but goal focused	Systematically observing and analyzing a system can provide insight into needed change. But this should not overly distract from staying focused on critical goal striving and system supporting functions.

Figure 1. Network Goal Analysis of Team's Goal Pursuit Mechanisms

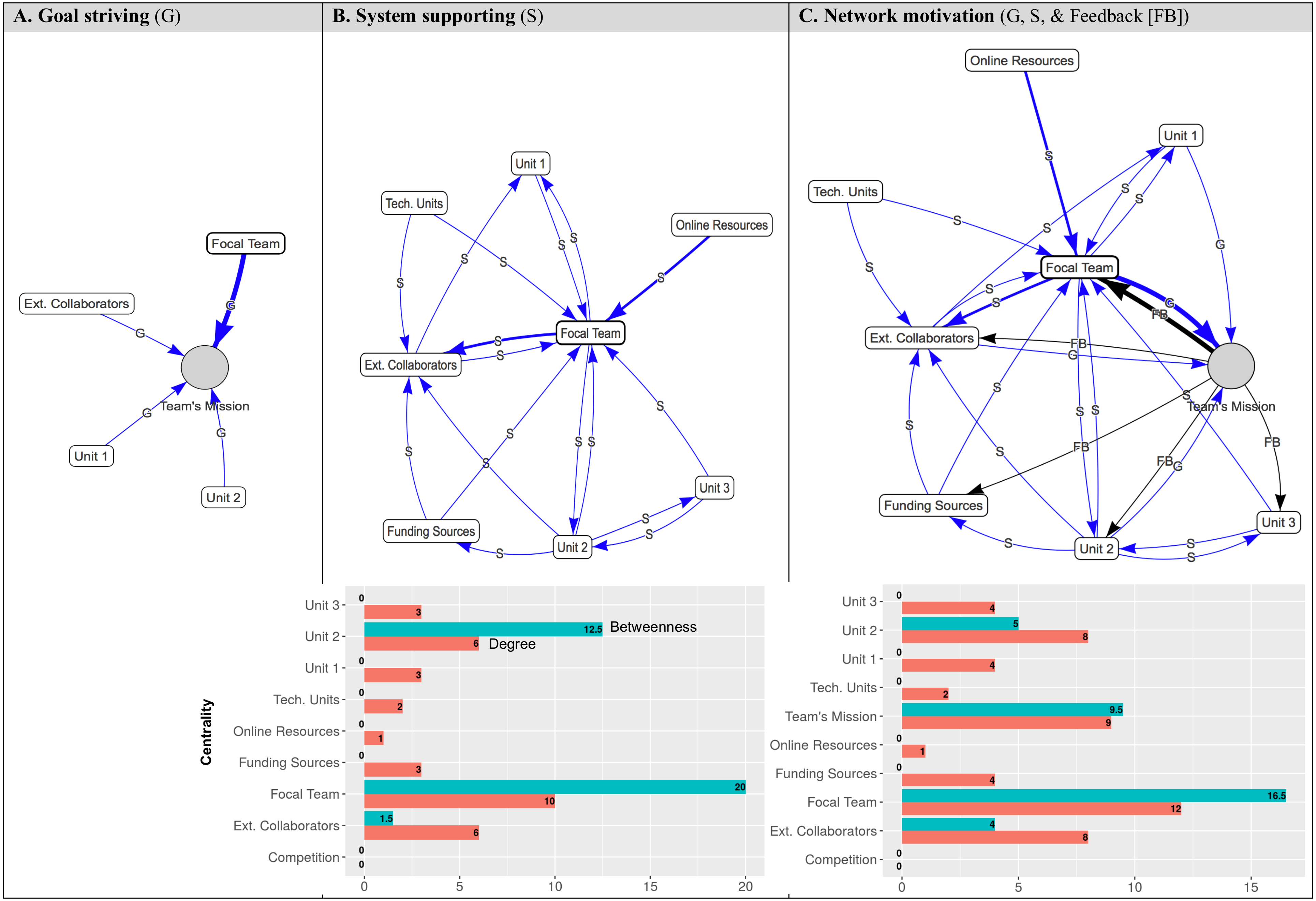
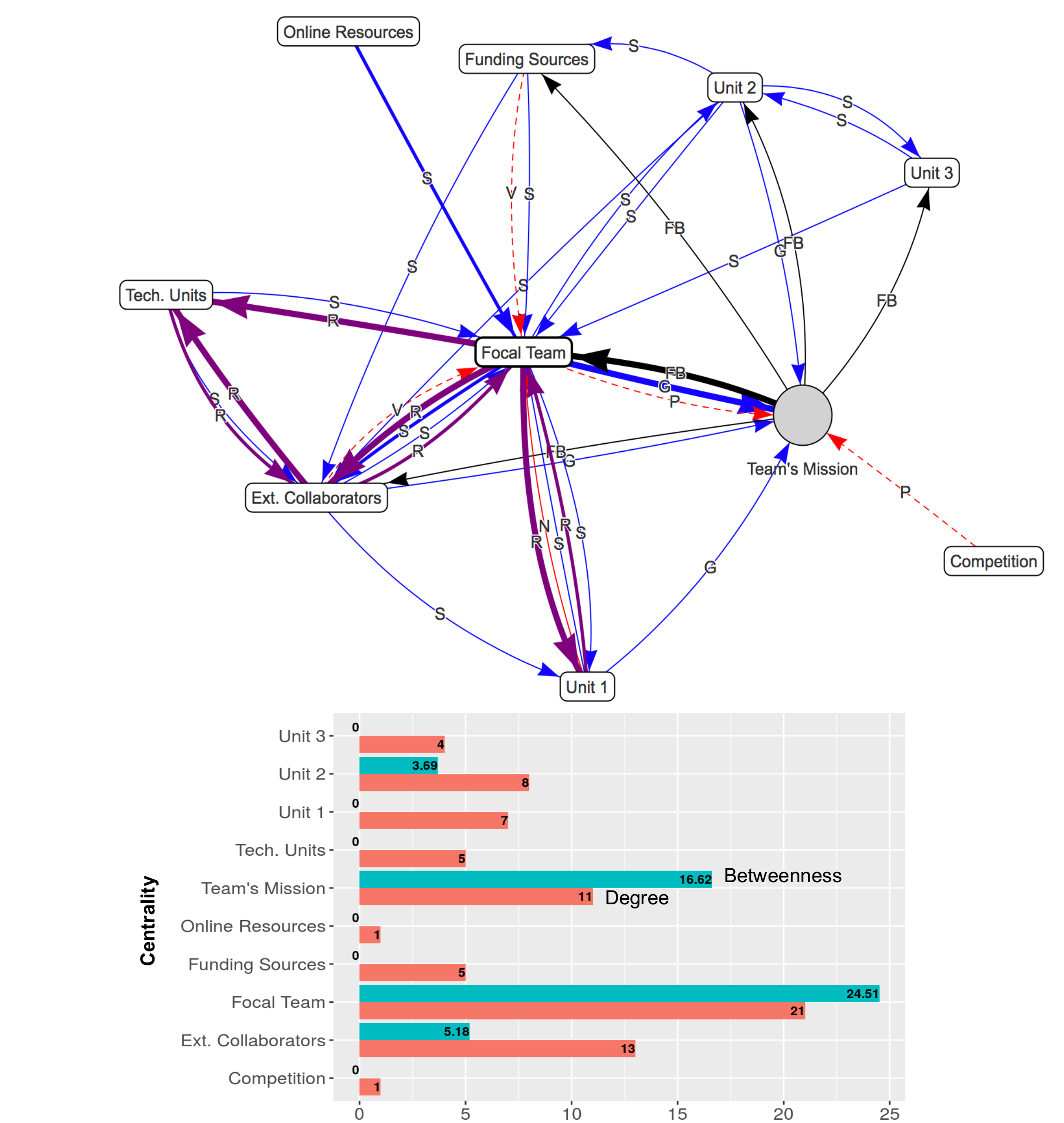
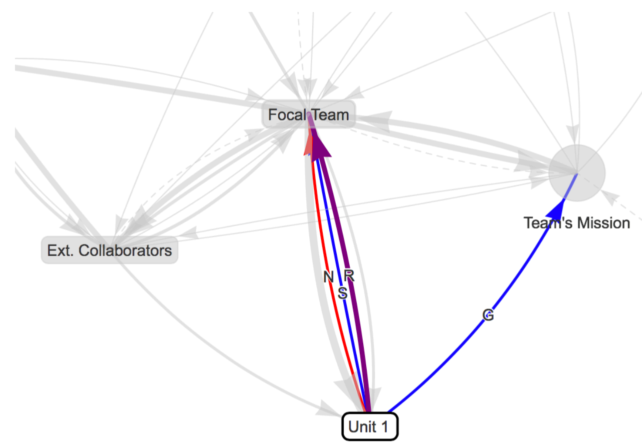


Figure 2. Network Goal Analysis of Team's Full System Relations and Example Individual Sub-Analysis.

A. Full System (G=goal striving, S=supporting, P=preventing, V=sup. resisting, N=negating, R=reacting)



B. Example Individual Sub-Analysis (outdegree)



Calculation notes for Unit 1. pot. = potential.
All links dichotomized as absent = 0, present = 1.

Role	Ratio	
G	1.00	(1 G link) / (1 max pot. goal node recipient of Unit 1)
S	0.13	(1 S link) / (8 max pot. social recipients of Unit 1)
P	0.00	(0 P links) / (1 max pot. goal node recipient of Unit 1)
V	0.00	(0 V links) / (8 max pot. social recipients of Unit 1)
N	0.13	(1 N link) / (8 max. pot. social recipients of Unit 1)
R	0.13	(1 R link) / (8 max. pot. social recipient of Unit 1)
Volume	**Ratio**	
2	0.22	(# of observed entity or goal node recipients) / (Max pot. recipient entities including goal nodes): 2 / 9
Multi-plexity	**Ratio**	(Multiplexity observed between entities) / (Max observed entity recipients including goal nodes):
1.25	0.63	((3[NSR] links / 4[SVNR] max pot. links to Focal Team) + (1[G] link / 2[GP] max pot. links to goal)) / (2 observed entity recipients [Focal Team & Team's Mission goal node]) = (.75+.50) / 2
Com-plexity	**Ratio**	Complexity: Volume x Multiplexity Ratio: 2 x .63
1.26	0.14	Complexity Ratio: Volume Ratio x Multiplexity Ratio: .22 x .63