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Closing Time: The Impact of Transitivity on Organizational Instant Messaging

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Abstract

We conducted an exploratory study of 25,260 instant messages from 14 interdisciplinary team networks focused on digital innovation with advanced machine learning technologies. We seek to contribute to theory on network embeddedness in such teams and find that the embeddedness of a message sender influences the messaging activity in teams. However, we further find that the influence of homophily vary depending on the topology of the network, and can contribute to the stratification of these network teams.

Keywords: Social Networks, Relational Event Model, Tertius Iungens, Digital Innovation Teams, Embeddedness [1]

1. Introduction

The generation of digital innovation occurs through collaborative, computer mediated team networks. Increasingly, cutting-edge digital innovation relies heavily on advanced machine learning based artificial intelligence technologies. Teams that are generating these sorts of innovations are intensely interdisciplinary, and seeking to embed computer scientists in a fundamental way within networks of traditional domain and technology specialists. An important question involves how the structure of these teams may influence the cross-disciplinary embeddedness of these advanced machine learning computer scientists.

In this research, we conducted an exploratory study of 14 interdisciplinary team networks that are generating digital innovations using advanced machine learning capabilities. We analyzed 25,260 messages from the instant messaging channel data of the team networks using Relational Event Modeling (REM) techniques. REM is well-suited for exploring network dynamics and the likelihood of events such as the edge formation among nodes in a network. It is a technique well suited for exploring the factors influencing the embeddedness of members of a team.

Our exploratory research is intended to generate theoretical insight, and can thus be considered a type of computationally intensive theory construction that involves an iterative approach to scholarship where researchers draw on existing theory and use computational techniques to contribute to this body of work [4, 26]. We draw on classic research on organizational network analysis [16] and computer mediated communications for collaboration [18, 36]. In particular, we leverage concepts of homophily, centrality, and triadic behaviors to understand these team dynamics. We find that embedded message senders are critical for driving the messaging activity necessary for the triadic closure that enhances the embeddedness of all members of the network. We caution, however, that this increased network density is not necessarily indicative of more inclusive networks, because homophily can continue to drive stratification among team members even in dense networks. The influence of homophily depends on the network topography. These findings question some of the prevailing assumptions in the study of innovation team networks.

2. Organizational Instant Messaging

The integration of Web 2.0 tools into the electronic social networks of organizations has afforded alternative communications channels outside of traditional phone calls and emails to include instant messaging (IM),

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video conferencing, shared document repositories, etc. [36]. These channels – referred to as computer mediated communications (CMC) – have grown over time in both media/channel (e.g., instant messaging and video conferencing) and scope (e.g., including external members). Geographically dispersed teams can often collaborate concurrently on different media of exchange or switch between CMC tools depending on the task and team communication norms [30].

Organizational research has long recognized the use of instant messaging (IM) for complex work discussions and expressive, flexible communication [18, 27]. This real-time and direct nature of IM affords "presence awareness," which allows colleagues to communicate more synchronously and productively by knowing when each other are online and available [37]. Research has shown that this presence awareness inherent to the synchronous nature of IM is a sufficient condition for effective knowledge sharing [24]. Thus, organizations must consider IM as essential for communications structure and knowledge transfer [36].

Wellman et al. (2001) contends that "computer networks are inherently social networks" and email networks have the ability to span geographic distance to facilitate interpersonal relationships [44]. Email networks have been shown to exhibit "small world" behavior that influences the spread of information through the network [13]. Several studies have similarly applied contagion theory to electronic networks to analyze the spread of information through computer mediated ties [13, 11]. Analogously to classical social network theory, studies have shown that "the way information spreads is affected by the topology of the interaction network" and spread is limited by how the topology increases path distance between actors [45].

3. Network Shapes

3.1. Topological Variation

Business problems have both (1) a substantive task and (2) an organizational/procedural problem [16], and studies have explored whether the same substantive task can be better solved by undertaking different social network shapes. This "network shapes" literature was born out of the idea in Bavelas (1948) that task success and satisfaction should be considered a function of the topological structure of small teams, where information spreads through a network structure from central to peripheral regions [3]. This hypothesis was tested by Leavitt (1951) and Shaw (1954) through experiments where cubicle workers passed notes through strategically positioned slots in the walls between them to solve a shared task [22, 39].

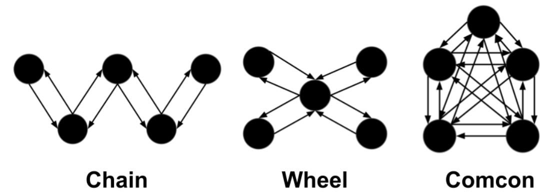


Figure 1. Paradigmatic network shapes as summarized from Leavitt (1951) and Shaw (1964)

The Chain, Wheel, and Comcon are three paradigmatic shapes of these networks (see Figure 1). There are other shapes mentioned in the literature, but these are variants of these main topologies. For example, Shaw originally described a Circle shape, but this can be considered as a derivative of a Chain with a connection between the first and nth actors. Studies have found that each shape has different types of organizational task challenges. The Comcon structure has to close off and specify which channels to use to avoid cross-communication; the Wheel needs the hub person to accept their role; and the Chain requires a more complicated relay system to pass information to all actors [16]. Further, we see implied hierarchy in each shape. The Comcon shape connects all actors with a distributed, flatter hierarchy. The Wheel displays a natural two-level hierarchy to a centralized leader. The Chain implies at least a three-level hierarchy such that peripheral actors don't communicate directly with the leader.

3.2. Topographies and Team Performance

There were varied and sometimes conflicting findings from the original "Bavelas-Leavitt" message-passing experiments concerning efficiency and performance. Shaw (1964) found no difference in the number of messages sent, group satisfaction and performance on the task, but a notable difference in time taken to reach a decision for different shapes [38]. Wheel structures were shown to produce higher performance and better efficiency, but lower satisfaction metrics than other network shapes [38, 22]. In addition to the increased performance of the Wheel, these studies found that Chain and Comcon structures offer lower performance and efficiency, respectively [22, 38].

Researchers also examine the effectiveness of each shape based on the complexity of the substantive task. Macy et al. (1953) increased difficulty of the substantive task by purposely introducing errors in the coding process and demonstrated that redundancy in a network structure can be a mechanism to reduce error rate [23]. Shaw (1954) found that Chain structures are better suited for complex problems since they distribute information access to more members, increasing the "possibilities for contribution" needed for complex tasks [39] . Centralized structures such as the Wheel structures face difficulties with complex tasks in which the central leader becomes so overburdened by a difficult substantive task that it inhibits their ability to function as the necessary hub of the organizational task [9].

3.3. Centrality

Centrality serves as a proxy for information availability and embeddedness in a communications network, impacting the degree to which an actor can contribute to the substantive and organizational tasks [22, 39]. Since individual centrality correlates with the amount of information an actor receives about a task, it affects the time to complete an activity and emergence of a leader [39, 31, 6]. But a completely centralized decision structure risks overburdening the leader by sheer volume of organizational work, causing information blockages [31].

Organizations can also err by trying to over-integrate peripheral subgroups into the decision structure, which instead overburdens every actor [21]. Without structured communications, the organizational task becomes harder by extensively increasing the amount of work for each actor [9]. However, recent studies on decentralization have shown promising results and there has been a shift towards strategic decentralization [10, 9].

4. Triadic Behavior

Classical theory on social capital and structural holes comes to the conclusion that the best way to optimize one's network is by undertaking triadic strategies. Simmel first identified the influence of the third over a dyadic relationship and Burt built his structural holes argument based on this influence/control [40]. Exploitation of information asymmetry at a structural hole is called *tertius gaudens* – i.e., the third who enjoys, where an intermediary promotes active separation of two parties (i.e., alters) to benefit from exclusive information from the alters. *Tertius gaudens* strategies are more often found in competitive markets [2] and among unfamiliar/less embedded actors [32]. But even in competitive markets, firms might seek a balance between embedded and arms-length ties as embeddedness provides heightened social capital which is more useful than immediate information benefits [41].

An orthogonal approach to triadic behavior is seen in the *tertius iungens* social strategy, where the intermediary acts as the "third who joins" two disconnected parties [28]. Here, the intermediary purposely closes the structural hole by introducing the two previously unacquainted alters or facilitating further interaction between two familiar parties [29]. In the latter case, embedded actors may have some type of existing ties with most people in the network, but they may not consider formal collaboration until a broker increases the level of trust in the relationship. *Tertius iungens* purposefully leverages these types of dense, embedded ties between all three actors in the triad to allow for trust, more granular information sharing, and joint problem solving [41].

Obstfeld (2005) also identifies teams engaged in innovation as being in a prime environment for applying *tertius iungens* to the "action problem," as organizations engaged in innovation must have some sparsity to generate new ideas, but people must be joined to produce coordinated action [28]. Employing a *tertius iungens* strategy can be especially effective in diverse and collaborative / non-competitive networks. This strategic addition of ties has been shown to work well in environments with cultural norms of openness, teamwork, trust, and reciprocity [2].

5. Research Method

5.1. Relational Event Modeling

Traditionally, network activity and triadic behavior has been measured via the distribution of survey instruments [46, 2, 28], but this type of data can be biased and is often costly to collect [19, 15]. Fortunately, the increased availability of electronic communication and event data has allowed for more fine-grained analysis of social interactions [20, 5]. From a dataset of 14.5M emails, Kossinets & Watts (2006) challenged traditional network theory with findings that (1) homophily did not have a significant effect on closing structural holes and (2) the social capital of these brokers seemed to average-out in large networks [20]. Quintane et al. (2013) [33] also found that short-term stability (in reciprocity and closure) is not necessarily subsumed into the long term patterns in traditional network analysis.

This increased data availability has spawned new methods through a revival of survival analysis in the Relational Event Modeling (REM) technique. Butts (2008) formalized REM as a way to model the trace data of communications with a Poisson process such that the probability of the next dyadic tie / relational event has the minimum hazard rate in traditional survival analysis [8]. Conditioning on the event history up to time $t-1$, the potential events at time t happen stochastically with different propensities based on their history of occurrence. The "risk set" at time t contains all possible dyads that might occur, and we can fit a Cox regression with a binary dependent variable of which event in the risk set actually occurred at time t.

5.2. Computationally Intensive Theory Construction

Studies leveraging REM have shown exploratory tendencies as researchers gain access to data at a new level of granularity that allows them to examine new relationships and address previously infeasible calls for examination of network dynamics [20, 33, 17]. We can exploit this increasingly abundant trace data via computationally intensive theory construction (CITC), which iteratively applies computational techniques with grounded theory and sensemaking to develop new theory [4, 26]. As we are considering areas with open questions (e.g., REM sampling and scaling) and/or conflicting theory (e.g., efficiency of Wheel vs. Comcon structures), we can take the trace data as ground truth and perform computationally rigorous sequential analysis to produce propositions. We aim to offer theoretical propositions for future research based on grounded network theory and patterns derived from sequential analysis.

6. Study

6.1. Data

We studied 14 teams that are working across universities and industry to generate machine learning applications for scientific discovery in chemistry. The teams were part of a broader, cross-disciplinary science organization, and team members were primarily from the fields of computer science (“CS”) or chemistry.

The teams display diversity of (1) tenure and (2) field of study. Teams vary in size from 3 to 17 members and display high variation in their personnel composition across the ranks of graduate student, assistant faculty, post docs, research scientists, staff, etc. While the organization is interdisciplinary across teams, each team tends to be homogeneous with respect to field as their is only one team member out of 114 working in a team different from their academic background. In order to code whether a researcher had a more formal background in the field of CS or chemistry, we examined the biographies, publication histories, and LinkedIn profiles of team members and validated our mappings with the organization’s leadership.

To conduct network analysis, we collected trace data from the Slack communications system used by the organization. We gathered timestamps of 25,833 direct messages sent among team members from its early usage on August 24, 2019 to a data checkpoint on February 29, 2024. Each message is a relational event consisting of a sender, receiver, and timestamp, which can be considered as a directed tie between two network actors. These trace data afford us the granularity to see the daily communication habits of team members, but we realize that we likely miss some of the offline communication that happens outside of these platforms (e.g. in-person conversations, emails, etc.). Despite the existence of offline communication, there is precedent for usage of email and messaging data for network analysis [13, 20, 33, 8].

To investigate whether different network shapes correlate with different communications habits, we map each of our teams to their nearest “Bavelas-Leavitt” topology [3, 22]. Although these network shapes were initially intended for small groups of 4-6 people passing paper messages at a table, we can generalize these topologies to include many geographically dispersed actors by considering the (1) average betweenness centrality, (2) overall density, and (3) a static snapshot of the network topology. We use betweenness centrality due to its similarity to the original experiments and findings that centrality is better measured via betweenness than network size/degree or closeness measures [14].

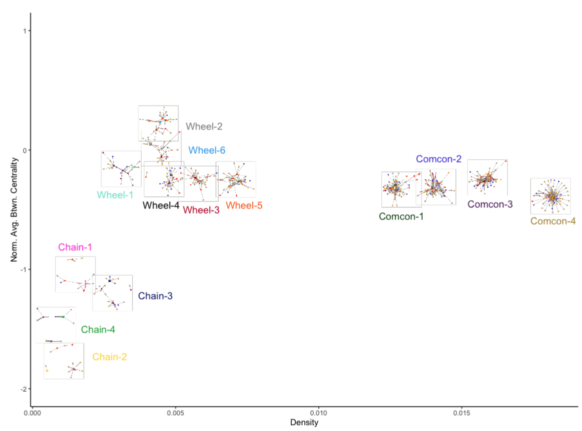


Figure 2. Plotting team topologies by Density and Avg. Centrality maps to paradigmatic shapes

We consider the three paradigmatic Bavelas and Leavitt shapes: Chain, Wheel, and Comcon. Chain topologies display low centrality and density such that each actor only messages 1-2 others with little redundancy. Wheel shapes are primarily characterized via a very highly centralized leader. Comcon structures also typically have relatively high centrality, but they are identified by their increased density and many redundancies as most actors are connected. With these criteria in mind, we can plot the density of the network by its average betweenness centrality for each team in Figure 2. Since density correlates highly with betweenness centrality (ρ = 0.9779), we normalize this value by the number of edges to capture the part of centrality not shared with density, decreasing their correlation to ρ = 0.3204. We can clearly see three distinct clusters with similar network shape images within clusters.

6.2. Network Statistics

We calculate several network statistics of interest to use as covariates in our REM, all of which can be found in Table 1. We are interested in triadic behavior, so we employ several different measurements of triadic closure. We calculate a General Closure metric as the strength of two-paths between some sender i and a receiver j through an intermediary k. When there are a lot of messages sent on the $i \rightarrow k \rightarrow j$ paths, we see frequent brokerage of information around messages between sender i and receiver j with a high General Closure value.

We are also directly interested in the *tertius iungens* activity, which closes structural holes or introduces new projects to a closed triad. We are unable to model the latter "existing iungens" activity, but we can consider the initial introduction of two actors who share a common contact. We create a First Closure statistic as a binary indicator of the first time that some sender i messages a receiver j with some shared k intermediary.

Transitivity and triad census consider the number of closed triads in a given network/subnetwork [43]. We would expect actors engaged in *tertius iungens* to have a high degree of local clustering and embeddedness in their immediate neighborhood (i.e., a high degree of transitivity) since *iungens* is enacted by the intermediary k connecting their mutual contacts. Calculating these Transitivity statistics for both Sender and Receiver, we can determine whether a given event/message $i \rightarrow j$ is likely to have resulted from local clustering / *tertius iungens* behavior by some neighboring intermediary k of sender i or receiver j.

Although we are primarily interested in triadic behavior, we also need to add network statistics to account for patterns at the node and dyad-levels which might also explain communications activity. In line with previous literature, we consider Inertia as the propensity for sender i to message receiver j based on the number of previous $i \rightarrow j$ messages exchanged. By symmetry, we also track Reciprocity as the tendency for sender i to message receiver j based on the number of previous messages in the opposite direction (i.e., $j \rightarrow i$). We also need to account for the general propensity for a given node to send or receive messages in the network. We calculate each node's Activity as the total number of messages that the actor has sent to any other node in the network and its Popularity as its total number of messages received, which correspond to each node's out- and in-degree, respectively. Lastly, we want to consider time-invariant features of each node including a given node/actor's rank (e.g., PI, grad student, post doc, etc.), field (i.e., CS or chemistry), and which team they are affiliated with. These fixed effects also lend themselves to binary homophily metrics that account for whether an $i \rightarrow j$ message occurs between two actors of the same rank, background, or team.

7. Models and Results

Relational Event Modeling (REM) can be seen as an implementation of survival analysis by applying the Cox Proportional Hazard Model (CPHM) to a particular data structure of events, which we will call the Sampled Event History (SEH). In a large network with $|V| = 114$ actors, it would be computationally infeasible to calculate sequential network statistics for the entire risk set of $|V|! \ / \ (|V| - 2)! = 12,882$ potential directed dyads for each of $N = 25,260$ relational events. Thus, at each time period t, we randomly sample 20 control events for each event/message, which meets the recommended threshold in Schecter & Quintane (2020) for stable parameter estimates [35]. Then, we calculate each of the network statistics in Table 1 above and exponentially weight all of our statistics using a half life of three days (from related literature) and standardize them to ensure scale of the network statistic does not impact our coefficient values [33, 42]. These weighted, scaled network statistics serve as covariates in a Cox regression for the event dummy variable for whether an event in the case-control SEH actually happened.

As mentioned above, we consider three levels of network statistics in our modeling process. At the node-level, we consider Activity and Popularity as these are calculated with respect to a single actor and how they individually interact with the rest of the network. The dyad-level statistics include Inertia, Reciprocity, In-Team, and homophily measures (i.e., Same Rank or Same Field) since these characteristics are present in the messages sent between two particular nodes i and j. We are primarily interested in our triad-level statistics including general closure, first closure, Sender Transitivity, and Receiver Transitivity as they are enumerated across sender i, receiver j, and their intermediary(ies) k.

Lastly, we consider fixed effects for characteristics of nodes regarding their rank (e.g., PI, grad student, etc.), field (i.e., CS or Chemistry), and team affiliation. However, we find high multicollinearity between (1) field and team – since only one team has an interdisciplinary member – and (2) rank and team – since personnel varies

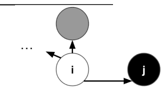
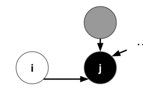
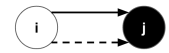
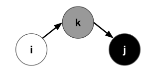
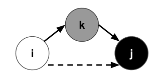
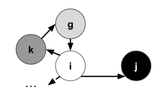
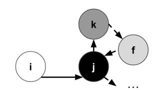
Statistic	Definition	Level	Formula	Visualization
Activity	tendency for i to send a message to j based on i's previous number of messages sent in the network	Node	$X_{ij}^{\text{act}}(H_t) = \sum_k n_{ikt}$	
Popularity	tendency of j to receive a message from i based on j's history of receiving messages from all members of the network	Node	$X_{ij}^{\text{pop}}(H_t) = \sum_k n_{kjt}$	
Inertia	tendency of i to send a message to j based on the past number of messages i has sent to j	Dyad	$X_{ij}^{\text{int}}(H_t) = n_{ijt}$	
Reciprocity	tendency of i to send a message to j based on the past number of messages i has received from j	Dyad	$X_{ij}^{\text{rcp}}(H_t) = n_{jit}$	
General Closure	the tendency for i to send information to j via an $i \to k \to j$ path through some k intermediary(ies)	Triad	$X_{ij}^{\text{gcl}}(H_t) = \sum_k n_{ikjt}$	
First Closure	whether this message would be the first between i and j, with an existing $i \to k \to j$ path through some k intermediary(ies)	Triad	$X_{ij}^{\text{fcl}}(H_t) = \mathbb{1}\{\exists k : i \to k \to j \in H_t \ \wedge \ i \to j \notin H_t\}$	
Sender Transitivity	ratio of closed triangles ($i \to k \to j \cap i \to j$) to possible triangles ($i \to k \to j$) which i initiates	Triad	$X_{ij}^{\text{str}}(H_t) = \frac{\sum_{k \to g} n_{kgit}}{\sum_{k \to g} n_{kgt}}$	
Receiver Transitivity	ratio of closed to possible triangles which j terminates	Triad	$X_{ij}^{\text{rtr}}(H_t) = \frac{sum_{f \to k} n_{jfkt}}{\sum_{f \to k} n_{fkt}}$	

Table 1. Network statistics calculated from the SEH and used as covariates in REM

across teams in a way that less common ranks (e.g., Staff, Postdoc) uniquely map to a single team. However, past studies have used stratification on individuals to remove the dummy variable coefficients from the partial likelihood function of a Cox regression and still solve this omitted variable issue [1, 12]. We perform this stratification at the team level to account for the effects of rank and field.

7.1. REM Results

We build a series of nested models to demonstrate the improvement in fit as we add network statistics by level. We start with a simple REM **Model 1** that only includes our node-level statistics activity and popularity along with fixed effects. We are not surprised to find that coefficients in each model are all very statistically significant (i.e., p<2e-16) since we are testing against the null hypothesis that events in the network occur randomly. Coefficients greater than zero contribute to an increase in proportional log likelihood of an event happening with respect to the baseline rate.

Model 2 adds dyad-level statistics, refining our focus from messages from some actor u to the entire network to consider messages between specific pairs of senders i and receivers j. **Model 3** that controls for other network event patterns and fits the data better (AIC = 19.0302) than both of our naive models.

Looking at the **Model 3** coefficients in Table 2, we see that Sender Transitivity ($\theta_{str} = 1.4430$) and Same Rank ($\theta_{sr} = 1.0949$) have the highest magnitude impact on the proportional likelihood of a relational event (i.e., a Slack message). Put simply, messages occur much more often between (1) embedded actors and (2) actors of the same rank. We also note that our other homophily and transitivity statistics – i.e., Same Field ($\theta_{sf} = 0.6138$) and Receiver Transitivity ($\theta_{rtr} = 0.3531$) – score relatively high coefficient values but are also comparable to our fixed effect for Send PI ($\theta_{rtr} = 0.4042$). On the opposite end of the figure, we find that the coefficient for the binary indicator First Closure has a very small value ($\theta_{rtr} = -3.2338$), indicating that introductions between actors with a shared intermediary is understandably rare – as first impressions are washed out by regular messages.

7.2. Results by Shape

To explore whether networks with varied topological structures demonstrate different communications patterns, we group teams by their shape and estimate separate REMs for each shape. Figure 3 provides three different REM coefficient estimates on the x-axis for

	Model 1: Node			Model 2: Node+Dyad			Model 3: N+D+Triad		
	Coef.	**SE**	**z**	**Coef.**	**SE**	**z**	**Coef.**	**SE**	**z**
Sent by PI	1.2162	0.0146	83.47	1.4478	0.0152	95.30	0.4042	0.0164	24.62
Activity	0.0747	0.0032	23.54	0.0634	0.0049	12.82	-0.0334	0.0058	-5.77
Popularity	0.2415	0.0031	78.79	0.2212	0.0039	57.28	0.0859	0.0058	14.86
Inertia				-0.1004	0.0052	-19.23	0.0160	0.0068	2.37
Reciprocity				0.1000	0.0032	31.38	0.0875	0.0035	25.22
In-Team				0.2391	0.0189	12.68	-0.0610	0.0208	-2.93
Same Field				0.5217	0.0219	23.87	0.6138	0.0226	27.12
Same Rank				1.3833	0.0141	98.20	1.0949	0.0139	78.58
General Closure							0.1097	0.0029	37.31
First Closure							-3.2338	0.0497	-65.09
Sender Transitivity							1.4430	0.0109	131.88
Receiver Transitivity							0.3531	0.0034	104.71
Model AIC			3.8028			11.8411			19.0302

Table 2. REM coefficients, standard errors (SE), and z scores from the three nested models

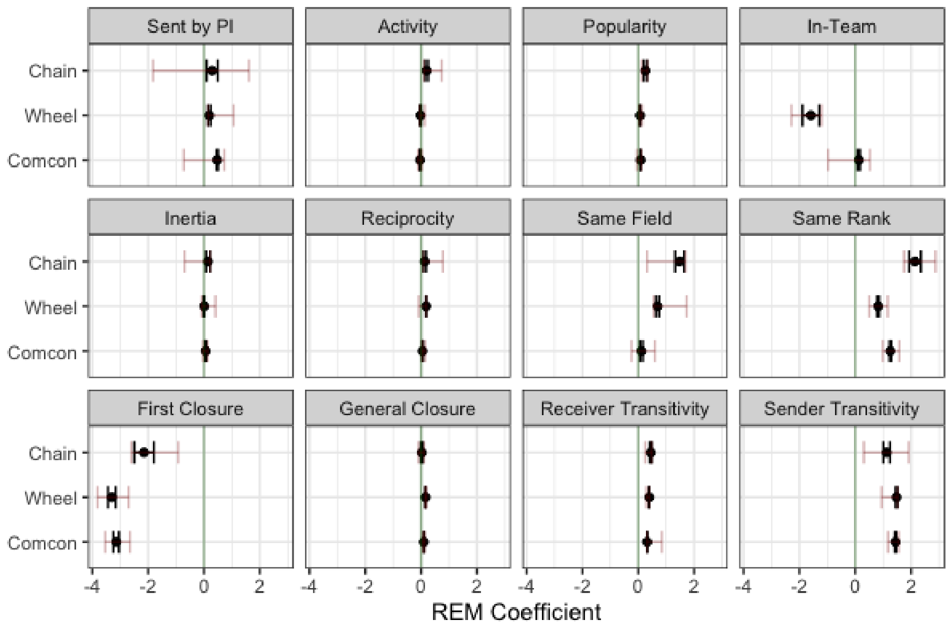


Figure 3. Coefficient values for REM fit on on each shape – robust confidence intervals are included in red

our respective shapes on the y-axis. In addition to the baseline hazard rate in green and the standard $\alpha = 0.95$ confidence interval (CI) in black, we also include an extended bootstrap-robust CI in red. In this robustness exercise, we again estimate a REM for each shape but leave one of the teams out each and take the largest and smallest values from these λ CIs as the bounds for the bootstrap-robust CI. However, we appeal to (1) the separation of clusters and (2) the visual similarity of network topologies in Figure 2 such that the black standard 95% CI is more likely than the robust red bars.

Examining the values across shapes, we notice interesting trends on the dyad and triad-level statistics. First, we find that none of the teams in the Chain shape send in-team messages, leading to a NA coefficient in the top right subplot. But we also see that unlike the Wheel structure ($\theta_{il} = -1.5905$), the denser Comcon teams are actually integrating in-team messaging as indicated by the increased proportional likelihood of the In-Team coefficient for Comcon ($\theta_{il} = 0.1306$) – and this difference is even fully robust to our bootstrap procedure. Further at the dyad-level, we see trends in rank and field homophily which vary across shape. Chain teams display the highest homophily tendencies for both field ($\theta_{sf} = 1.4785$) and rank ($\theta_{sr} = 2.1371$), with the latter being bootstrap-robust. But we note an interesting asymmetry in Wheels and Comcons such that Comcons display higher rank homophily ($\theta_{sr} = 1.2568$) but lower field homophily ($\theta_{sf} = 0.1107$). This finding is interesting since denser networks like Comcons are often praised for reducing hierarchy, but we see these increased ties occurring with rank stratification.

Finally, we show a bootstrap-robust finding that Chains are displaying a higher marginal effect for First

Closure – albeit at a low magnitude. Perhaps we see increased via *tertius iungens* brokerage behavior in which disconnected actors are introducing common contacts. Although the sparsity of these Chains supplies more opportunities for first messaging, actors seem to be capitalizing on these opportunities at a higher rate than the denser Wheels and Comcons.

8. Theory Development

8.1. Transitivity

REM coefficients are indicative of how certain network statistics drive change in topology due on their relationship to the proportional likelihood of which new ties will occur. Based on our findings in Table 2, we see Sender Transitivity as best predictor of the likelihood of a relational event in the overall network since it has the largest coefficient magnitude. When considering message patterns on the aggregate / entire organization level – i.e., across teams in an interdisciplinary innovation context – we consider Sender Transitivity to be the primary driver for how the network changes over time.

It is difficult to identify the triadic behavior that led to these closed triangles in this network. First Closure actually occurs more in sparse Chain shapes with lower density and lower transitivity such that transitivity does not seem to move with the introductory / new contact facet of *tertius iungens*. But we also observe the relative unimportance (with respect to the baseline rate) of General Closure across all shapes. Further, this tendency to pass information directly – rather than through an intermediary, was previously found to not correlate with transitivity in the data. Future research should consider whether these triangles close through purposeful triadic behavior, via some other mechanism, or purely stochastically.

Thus, we focus our theory development on the outcomes of transitivity – i.e., the increased embeddedness of the actor. Network ties are activated by messages between actors, so it makes sense that more embedded actors (i.e., with higher local transitivity) are driving network activity. Further, denser shapes integrate in-team messaging and are more likely to break field homophily and message external actors with interdisciplinary such that their embedded actors seem to be key players in the aggregate organizational network. Based on these results, we offer the Proposition:

> **P1**: *Embeddedness of the sender drives messaging activity at the organizational level across interdisciplinary subgroups engaging in innovation.*

8.2. Homophily

Homophily also generally helps explain messaging patterns at both the organization and shape levels. We note that rank and field homophily are the second and third largest coefficients in the center-level model and display difference in mean across all shapes at $\alpha = 0.95$. This homophily between actors is long established in network diversity literature [25, 34, 31].

We find that all shapes still display relatively high Sender Transitivity across paradigmatic shapes, but we do find differences in different shapes homophilic tendencies and integration of in-team messaging. Denser Comcon topologies integrate in-team messaging but display lower field homophily. Due to the near pure homogeneity of field membership in teams, this is surprising since increased in-team messaging might imply increased field homophily as chemists talk to chemists more often (and vice versa). However, we note that in-team messaging and field homophily only correlate $\rho = 0.1473$, so it is unlikely that our REMs are affected by multicollinearity between them. Thus, external communications (i.e., to members outside the team) of Comcons must display some level of interdisciplinarity to achieve this lower field homophily estimate with increased in-team messaging.

Further, we find another interesting trend as there seems to be more rank homophily in these denser networks as ties are more likely to arise between members of the same tenure. Existing literature contends that increasing density reduces hierarchy as it connects actors and eliminates the information asymmetries that create structural leadership and brokerage positions [16, 7]. Our finding is interesting since it shows that unlike traditional concepts of density, dense networks might not be reducing hierarchy or democratizing information flows. We show that increasing density is not necessarily reducing hierarchy in the practical sense as there is still a higher level of rank homophily. Instead we might take a more nuanced view on what hierarchy means in a network context when we also consider implicit tenure / rank as node characteristics. Thus, we propose:

> **P2**: *Rank homophily reinforces social stratification on tenure at both the organizational and subgroup level, even as network density increases*

9. Conclusion

In this study, we reviewed how different network shapes might influence a team network's dynamics around triadic closure which would be associated with the embeddedness and inclusivity of a team. We outlined triadic strategies that individual actors may undertake to influence overall network topology. We drew on a REM analysis of 14 team networks, and using these findings, we generated theory that can be tested by future studies to advance understanding of network dynamics.

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11. References

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