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Team talk: Learning, jargon, and structure versus the pulse of the network

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ABSTRACT

We began this work intending to illustrate the network origins of jargon, a signal feature of team learning and the division of labor. In the process, we came to recognize the substantive importance of message timing, which we discuss as the pulse of a network. This paper describes our route to that recognition. We analyze data from a renovated classic network experiment providing empirical support for three hypotheses. The first, and most familiar from past work, is that teams moving down their learning curve to greater efficiency are prone to shared jargon. As a team moves down its learning curve, language drifts away from day-to-day speech, into jargon. The second and third hypotheses concern network correlates of the drift. With respect to network structure, teams are less likely to converge on jargon when communication is concentrated in one teammate. With respect to pulse, teams are more likely to converge on jargon when communication efforts are numerous and crowded in time. The two network predictors overlap conceptually. They both involve learning and access to information, but are distinct in their mechanism: Structure provides access. Pulse creates motivation to access. Teammates keeping up with numerous messages concentrated in time have a shared incentive to find shorthand terms (i.e., jargon) that enable faster exchange of accurate information. Network structure predicts team convergence on jargon, but pulse is a stronger predictor. Directions for new research are discussed.

1. Introduction

How does the social network within a group affect the emergence of jargon enabling the group to perform more quickly and effectively? In the process of addressing this question, we add network pulse to familiar concepts of network structure predicting team performance. We speak in terms of a team, but for other audiences we could equally well speak in terms of group, council, assembly, or some other noun referring to a set of people interacting on some activity. The interaction could be physical or virtual. The activity could be a formal assignment, voluntary collaboration, or frequent socializing in a neighborhood hang-out.

By "jargon" we refer to words or expressions used by insiders with specific meaning not obvious to outsiders. We are guided in our analysis by the image that as colleagues work with one another, they adopt terms — jargon — to codify their shared experience. Jargon can index knowledge that would be difficult, or unnecessarily time-consuming, to describe in generally understood language. By so doing, jargon lowers the personal effort needed to mentally engage team-relevant information, increasing the volume of information colleagues can exchange per unit communication. Jargon becomes the tip of a knowledge iceberg. Implicit in a jargon term is a cluster of activity. Put a surgical instrument in the hands of an experienced surgeon and she knows immediately the social situation for its use: the people in the room, the step preceding the instrument's use, who will do what during the use of the instrument, the step that follows use of the instrument. No need to state these bits of information. For the cognoscente, the information bits are implicit in the jargon. The same amount of information would require a fulsome text to communicate with an outsider. The above is an image familiar across the social sciences (e.g., Arrow, 1974, on work "codes" in an organization, David, 1994; Zucker, 1977, on institutions as the carriers of history; Garfinkel, 1967, on "indexical" meaning, Mills, 1940, on "vocabularies of motive," Schein, 1990, on language "artifacts" of organization culture, and, of course, Whorf, 2012, broad connection in linguistics between experience and speech). In short, jargon is an index to the division of labor. The more specialized the work, the more specialized the language. Jargon and its correlates, so viewed, are a signal element in contemporary civilization.

If jargon is such a signal element, why has it received so little attention in management research — and that little bit usually a negative remark in passing? A search for the word "jargon" in titles and

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abstracts (or key words if search through abstracts is not available) of several leading management journals returned no hits, except a 1999 book review in the *Academy of Management Review* extolling the reviewed book for its lack of "academic jargon."[1] Jargon is more discussed than written about. A search through the Academy of Management Proceedings returned ten hits, seven of which were denunciations of jargon ("behavioral science jargon," "business jargon," "consulting jargon," "jargons of different disciplines," or "research jargon"). The other three hits were a paper on the importance to network brokerage to understanding jargon in the target audience (Lampe and Reerink, 2021), an unpublished paper about creating pidgin language to facilitate brokerage despite local jargon (Sargent, 2018), and an Academy "best" symposium entirely about jargon, the title of which communicates a perspective consistent with the above negative views (Siltaoja et al., 2018), especially the lead presentation later published as "Bullshit in Organization Studies" (Christensen et al., 2019).

Lack of explicit attention does not imply irrelevance. There is a great deal of research from which one can draw inferences. Here is a roadmap to our argument in three sections, corresponding to our three hypotheses about jargon. In "Drift into Jargon" we establish our dependent variable by describing how high-performance teams are the ones that converge in their use of jargon (measured as percent of words in final messages that are jargon). Next, in "Network Structure Behind the Drift," we report on the network predictor inherited from past research. Teams in which communication is more centralized in single "leader," are less likely to agree on shared jargon, and accordingly turn in weaker performance on the complex task used here. Third, in "Drift into Jargon Driven by Network Pulse," we describe how our best network prediction comes not from structure, but from network pulse. The more teammates pressure one another for quick, accurate information, the more likely they converge on shared jargon.

In all three sections, we use a traditional theory, data, results format. In the spirit of transparency, however, we hasten to add that we did not anticipate the importance of network pulse. Using data previously collected in a team network experiment, we began studying jargon as a correlate of team performance. Network pulse emerged in our analysis as an important predictor. In retrospect, pulse could have been expected in theory to be an important network predictor, which is how we present it here — laying a foundation in theory for subsequent work on networks as predictor in both structure and pulse. With a baseline model of the generative process in place, we turn at the end of the paper to promising directions for future research.

2. The drift into jargon

From the network-information premise that underlies much of network theory in management, we expect teams to show a learning curve in which team discussion converges on jargon. The premise exists as two facts established during the 1950's "Golden Age" of social psychology (especially Festinger et al., 1950; Asch, 1951; Schachter, 1951; Katz and Lazarsfeld, 1955): (1) people cluster into groups as a result of interaction opportunities defined by the places where people meet; and (2) communication is more frequent and influential within than between groups such that people in the same group develop similar behaviors and beliefs. The network-information premise has a history in the sociology of mobilization (Festinger et al., 1950), marketing (Katz and Lazarsfeld, 1955), and polarization (Coleman, 1957). The premise is foundation for the small-world phenomenon (Milgram, 1967; Watts, 1999), and the competitive advantage of network brokers arbitraging information across groups (Kwon et al., 2020; Burt, 2021; Brass, 2022; Van Burg et al., 2022). Characterized by their location in social structure, connecting otherwise separate groups, network brokers correspond to Merton (1968); Gouldner (1957) "cosmopolitans," Katz and Lazarsfeld (1955) "opinion leaders" (see Burt, 2005:84-86, on network brokers versus opinion leaders), and, more distantly, Schumpeter (1934) and Hayek's (1937, 1945) touchstone images of what it means for a person to be an entrepreneur (Burt, 2005: Chap. 5, for network discussion).

Interpersonal influence and peer pressure are characteristically mentioned as responsible for the shared behavior and beliefs within groups, but similarity can result from no more than contact and courtesy. People in conversation with another person can, out of courtesy, try to express their point from the other person's point of view. Reciprocation and repetition will lead two speakers to a shared language expressing their shared point of view, and that coordination repeated with a broad selection of others in a group will result in a shared group point of view (Krauss and Weinheimer, 1964; Clark and Wilkes-Gibbs, 1986; Garrod and Doherty, 1994, for illustrative evidence; Centola and Baronchelli, 2016, for contemporary evidence). Whether by influence or courtesy, people tire of repeating arguments and stories explaining why they believe and behave together the way they do. They adopt jargon phrasing, opinions, symbols and behaviors that enable the group to operate more quickly with less effort, and define what it means to be a member of the group. Experienced groups, on average, display a learning curve as they operate more efficiently (Argote, 1999, for general review). Often cited examples are soccer teams, basketball teams, surgical teams, race-car pit crews, emergency teams, swat teams, elite assault teams — any group that performs better with tight integration among teammates (see Clark and Wilkes-Gibbs, 1986:13-14; Weber and Camerer, 2003:409-411, for illustrative learning curves in linguistic coordination; Burt, 2005:Chps 3-4, for review of the network mechanism responsible). Beneath the current jargon are new, emerging understandings and experiences awaiting a label, the emerging items more understood than said. What was once explicit knowledge interpretable by anyone becomes tacit knowledge meaningful primarily to insiders. With continued time together, information in the group becomes "sticky" – nuanced, interconnected, implicit meanings difficult to understand outside the group (Von Hippel, 1994). In summary of the above, our first hypothesis is about the link between jargon and team efficiency:

Hypothesis 1. Teams moving down their learning curve to greater efficiency are likely to create shared jargon.

2.1. Different jargon in different groups

The hypothesis is about consensus, not content. We are not looking for shared meaning in the jargon adopted, as one might in an analysis of sensemaking or organizational logics (Weick et al., 2005; Loewenstein et al., 2012). Shared meaning is a level of analysis deeper than, if informed by, our focus on consensus. Further, our focus on in-group consensus does not imply consensus across groups, even groups doing similar work. Depending on history, context, and personalities, two groups doing similar work can drift into different social conventions, from which they drift into different jargon. For reasons of a division of labor in which groups specialize on separate bits of work, or variation due to the independent evolution of separate social groups, holes tear open in the flow of information between groups. These holes in the social structure of communication, or more simply "structural holes," are missing relations indicating where information is likely to differ on opposite sides of the hole and therefore not flow easily across the hole. Two company divisions, doing related work independent of one another, can be expected to evolve to different ways of doing the business (Dougherty, 1992). Not every group needs be linguistically distinct, but when big information differences happen, they will be across groups, not within (see Pachucki and Breiger, 2010; Vilhena et al., 2014, on

[1] Journals searched: Academy of Management Annals, Academy of Management Discoveries, Academy of Management Journal, Academy of Management Review, Administrative Science Quarterly, Journal of Management, Management Science, Organization Science, and Strategy Science. The searches were executed on November 23, 2021.

"cultural holes" corresponding to "structural holes"). Thus, we have no expectation that independent teams doing the same task converge on the same jargon. Indeed, it would be a surprise if they did, given the idiosyncrasies of personal experience in which jargon is embedded. And once separate groups have drifted into different jargon, the local knowledge indexed by their different jargon is the core of what we know as sticky information, the fodder for network brokerage (Burt, 2021; Goldberg et al., 2016; Tasselli et al., 2020).

Weber and Camerer (2003) offer a minimalist experiment to illustrate the tendency toward different jargon in different groups (see Salganik et al., 2006, for more fulsome illustration; Konig et al., 2018, on CEOs communicating beyond their organization, and Guilbeault et al., 2021, on small groups being more prone to variation between groups). Weber and Camerer randomly assign students to teams of two. Each student is given 16 photographs of different office environments. A trial begins when student A is given a random sequence of eight of the photos, and asked to describe the eight to student B so that B can reproduce the eight-photo sequence. Student B, looking at the 16 photos, has to identify the eight being discussed and arrange them in correct sequence. On the next trial, Student B has the task of describing a new sequence of eight photos to Student A.

Over the course of 20 trials, the average 249 s required to complete the first trial decreases to 48 s for the 20th trial (Weber and Camerer, 2003:409). Trial time is shortened by using key words — jargon — that identify photo features. Weber and Camerer (2003:408), note that the jargon words: "…can be extremely idiosyncratic, because they seize on distinctive shards of language developed in the long initial descriptions, or on shared experience within the pair, which is unlikely to be common to outside observers. This process results in sound bite descriptions that often focus on different aspects of the pictures in different pairs. For instance, the picture called "PowerPoint" by one group was called "Woman sitting, smiling" and "Guy hunching" by other groups. It is unlikely that members of one group would be immediately aware of which picture the other group was referring to by hearing their description."

Performance deteriorates when — on trial 21— a third person is added to the team from a separate team that had completed 20 trials. On average, coordination among the three people in trial 21 requires 271% more time than was required on the 20th trial. The increased time is not due to the increased team size.[2] Weber and Camerer (2003:408,409), attribute the deterioration to the fact that the added third person had learned different jargon when working in a different team. When people from two teams are combined, extra time is needed to coordinate across the different jargon learned in the separate teams. No aspect of the experiment design creates different jargon in different teams. Idiosyncratic events in time and teams result in different jargon emerging in different teams, creating a barrier to merging teams.

2.2. Jargon pathology

Jargon differences between groups mark a portal to jargon pathologies. Pathologies are beyond the scope of this paper, but they have been so much the focus of the little attention given to jargon, and they extend the network theory here to such an interesting range of related phenomena, that we want to clearly mark the portal. As jargon indexes a cluster of knowledge for insiders, its use also signals among insiders a sense of shared membership, of community. Among outsiders, that same jargon use is a verbal claim to being an insider. Jargon is likely to be misunderstood among outsiders when they interpret jargon terms according to their meaning in the general population — which can make jargon look like nonsense to outsiders. Outsiders observing others' use of jargon are reminded that they do not belong, or perhaps do not have the right stuff to belong. Outsider reactions to insider jargon range from anger at presumptuous exclusion, to depression about being unworthy. Symptomatic pathologies include groups held together by debilitating jargon — with Adorno (1973) an iconic critique of intellectuals held together by overweening conviction in their jargon, and Vaughan (2016:252) an iconic documentation with respect to the Challenger disaster: "Language was fundamental to structural security at NASA. Talk about risk, in NASA culture, was by nature technical, impersonal, and bureaucratic — full of what to the uninitiated are meaningless acronyms, engineering terms, and NASA procedural references ["Action Item," "FMEA," "CIL," "waivers"]. Routinely used and taken-for-granted, the language did not lend itself to sending signals of potential danger." For more examples, see Loewenstein et al. (2012, search their text for "community" and "identity"). And, given the inevitable status ordering of groups, jargon will be used in lower status groups to signal aspirational membership higher in the hierarchy. For example, Brown, Anicich, and Galinsky (2020:277,279); show that acronyms more likely in the titles of dissertations and theses from lower-rank schools (and Spicer, 2018:37ff., on status-aspirational use of business jargon).

2.3. The experiment

Our data come from messages exchanged among teammates as they coordinate on a sequence of repeated tasks. The data are a by-product of renovating the Bavelas-Leavitt-Smith classic team coordination experiment (Leavitt, 1951). Burt et al. (2021) describe the renovated experiment, which involves communication through a computer interface, and competing leadership, as is often found in project teams. Subjects in behavioral research laboratories at Harvard and MIT are assigned at random to positions in five-person teams within which a network of communication channels is defined by restricting computer access between teammates (everyone can talk to everyone else, or all have to talk through a central teammate, or variations with two central teammates). Subjects only see messages to and from teammates with whom they are allowed to communicate. They do not see messages between their teammates, nor do they see the team network structure. Subjects assigned to a team participate continuously with the same teammates in the same network, and do not participate in subsequent teams. We return to network assignments in the next section.

Each team is asked to complete 15 trials. A trial consists of the five teammates, each receiving a "hand" of five symbols, with one symbol common to the hands of all five teammates. The shared symbol is selected at random for each team in each trial. The team task is to identify the shared symbol by sending online messages to one another. To simplify the task, the order of six symbols is constant in every hand of five symbols. At any time, a subject can submit his or her best guess of the shared symbol. Subjects know how many teammates have submitted answers (Burt et al., 2021:37, display the user interface), but do not know which teammates have submitted, nor what they submitted (unless the subject receives a personal message stating what a teammate submitted). When all five subjects have submitted their best guess, the trial is over.

Subjects receive a fixed payment plus an additional incentive payment for each trial in which they and their teammates all correctly identified their shared symbol. Subject compensation varied from $10 up to $31.25. One team had no correct answers in any of their 15 trials. Seven teams had correct answers in all 15 trials. Most teams were correct in 13 or 14 of the trials. Some teams collapsed before completing all 15 trials. We study messages within trials a team completed. Message content and timing were recorded, which provides our data consisting of 444,994 words in 74,861 messages between 385 subjects within 77 five-person teams, each playing up to 15 trials of the coordination task.

In the original experiment, teammates coordinated with respect to

[2] Control teams of three people reach the same efficiency as two person teams within 20 trials (Weber and Camerer, 2003:411), and across trials 21–30, the three person teams return to an average efficiency equal to the earlier average efficiency of two person teams (Weber and Camerer, 2003:409).

familiar shapes (circle, triangle, diamond, square, plus, star). In the renovated experiment, subjects coordinate with respect to six "tangram" symbols taken from Clark and Wilkes-Gibbs (1986:11), study of language coordination (the symbols will be displayed shortly). To coordinate on these symbols, teammates have to agree on a language by which symbols can be identified. The study goal was to address causality in network brokerage effects (Burt et al., 2021) and estimate network effects on language consensus (Reagans et al., 2020).

2.4. Results 1: Learning curves are evident

As expected from past research, the three solid lines in Fig. 1 show the teams moving down a learning curve. The line through solid dots shows teams completing each subsequent trial more quickly: an average of 11 min for the first trial, down to two minutes for the 15th trial (−0.99 correlation with ln(trial) in Fig. 1). The two lines through hollow dots and hollow squares show teams using fewer, shorter messages to complete each subsequent trial: an average of 147 messages containing seven words in the first trial, down to 37 messages containing four words in the 15th trial (respective −0.99 and −0.94 correlations with ln(trial)). The transition to more efficient work, visually obvious in Fig. 1, is statistically significant and robust to a variety of controls (Reagans et al., 2020).

The learning curves are relatively flat across the last three trials. To have a volume of text for comparing communication during initial and final trials, we sometimes combine messages during trials 13, 14, 15 and describe them as messages sent during a team's final trials. At the other extreme, we sometimes combine messages across trials 1, 2, 3 as messages during a team's initial trials.

2.5. Results 2: Language becomes unusual

As teams move down their learning curve to greater efficiency, the language in team messages becomes more unusual. Specifically, language becomes specialized to the team task. When subjects begin their work, they use familiar language — to the left in Fig. 2, similar to language in Twitter messages and articles in the *New York Times*. In subsequent trials, language drifts to the right in Fig. 2, away from the familiar.

To characterize the broad content of messages in Fig. 2, we use Pennebaker et al.'s (2015) Linguistic Inquiry and Word Count software (LIWC). The software treats text as a bag of words, counting the frequency with which index words occur. The software relies on a dictionary of several thousand index words and word stems that have been useful in diverse substantive applications (Tausczik and Pennebaker, 2010). Management network precedents include Burt (2010:256,264); using the positive and negative affect categories of LIWC to show that

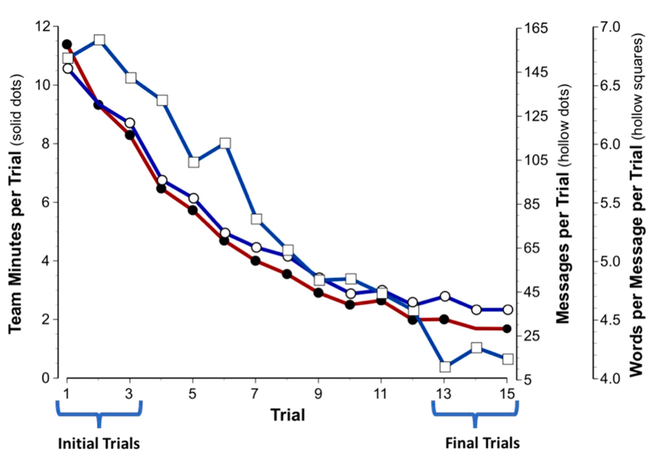


Fig. 1. Team Learning Curves.

when proposing ideas to senior management, network brokers are more likely to use a mixture of positive and negative emotions — rather than one or the other. Goldberg et al. (2016) compare the LIWC profile of a manager's outgoing email with the profile of his or her incoming email to show that managers who broker connections across groups enjoy more success when their profile of outgoing language matches the profile of incoming language from cited colleagues. Srivastava et al. (2018) show that managers for whom the profile match is poor are more likely to be fired. Burt (2017) shows that managers in more closed networks, argued to suffer from more severe temporal myopia, are less likely to use future tense when they describe opportunities or problems in the organization (also Opper and Burt, 2021).

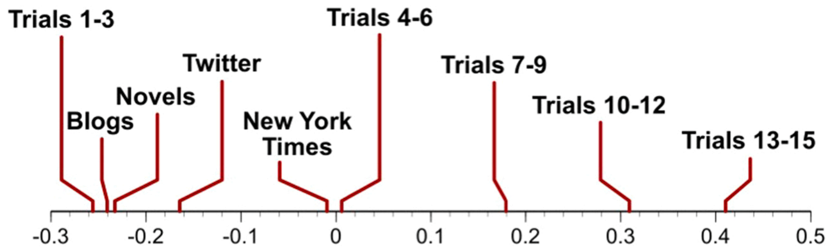
Texts are compared in Fig. 2 according to their LIWC profiles. LIWC output for a text includes a profile of 73 variables p_{tj}, where p_{tj} is the percent of words in messages during trial t that are in LIWC category j. For example, p_{tj} is 16.00 for the LIWC category "pronouns" during trial 1 — in other words, 16% of recognized words in messages during the first trial are pronouns. The 73 LIWC categories are (Pennebaker et al., 2015:2): "21 standard linguistic dimensions (e.g., percentage of words in the text that are pronouns, articles, auxiliary verbs, etc.), 41 word categories tapping psychological constructs (e.g., affect, cognition, biological processes, drives), 6 personal concern categories (e.g., work, home, leisure activities), 5 informal language markers (assents, fillers, swear words, netspeak)." In addition to the profile of 73 percentages, LIWC output includes counts of kinds of punctuation, number of words, percent of words captured by the LIWC dictionary (Fig. 1), and some summary language variables derived from the counts such as "analytical thinking" and "emotional tone."

For Fig. 2, we aggregate message words into five periods of three adjacent trials: messages sent during trials 1–3, messages sent during trials 4–6, and so on, up to messages sent during trials 13–15. We decided on the clustering of three trials based on similarities between adjacent trials, an interest in simplifying the presentation, and concern to provide a volume of text for LIWC analysis (Table S1 in the Online Supplement lists profiles for the five periods).

To compare profiles for Fig. 2, we compute the Euclidean distance between each pair of profiles, and submit the distances to a classical multidimensional scaling (Torgerson, 1958). Two text sources are close together in Fig. 2 to the extent that they have similar LIWC profiles. The profiles differ almost entirely on one dimension. The horizontal axis in Fig. 2 describes 96% of variance in the distances. The second dimension is negligible (2%).[3]

As a frame of reference for variation in messaging during the experiment, we include four familiar sources of text in Fig. 2. We take the profiles for these texts from the LIWC program manual (Pennebaker et al., 2015). In brief, "Novels" is a selection of novels tagged "literature" in Project Gutenberg (novels define "files" in Fig. 2), "Blogs" consists of posts from a variety of blogsites (bloggers define files), "Twitter" consists of tweets collected from the public profiles of users on the Analyze Words webpage (users define files), and "New York Times" consists of

[3] In the interest of replication, we note a choice in computing profile distances. The Euclidean distance between trials 1 and 2 is the square root of summed squared differences in the profiles for trials 1 and 2: $d_{12} = (\sum_j (p_{1j} - p_{2j})^2)^{.5}$, where j runs across LIWC categories. We use raw percentages output by LIWC rather than percentages normalized across categories. The LIWC percentage, p_{tj}, is the percentage of text words during trial t that are in LIWC category j. That percentage can be normalized as a portion of the total count: $p_{tj} / \sum_k p_{tk}$, where k runs across LIWC categories. We prefer the raw p_{tj} because the LIWC categories are hierarchical in that some words are often counted multiple times, so the normalized counts lose the meaning of the raw p_{tj} as category probabilities. From the program manual, for example (Pennebaker et al., 2015: 2): "the word *cried* is part of five word categories: sadness, negative emotion, overall affect, verbs, and past focus. Hence, if the word *cried* is found in the target text, each of these five subdictionary scale scores will be incremented."



	Files	Words
Novels	875	57,467,183
Blogs	37,295	119,449,058
Twitter	35,269	23,172,994
New York Times	34,929	26,007,632

	Messages	Words
Trials 1-3	30,690	207,231
Trials 4-6	19,515	118,855
Trials 7-9	12,109	62,340
Trials 10-12	7,045	33,510
Trials 13-15	5,502	23,058

Fig. 2. (a) Language Becomes Unusual, NOTE — Labels refer to sources of words sorted on the horizontal axis by classical multidimensional scaling of distances between LIWC profiles constructed from each source. (b) The one dimensional scaling captures 96% of variance in distances among the nine sources.

articles (front page, features, editorials, letters to the editor, etc.) published on the New York Times website (articles define files).

The left and the right of the spatial display are substantively significant. The left side shows that team messages begin with familiar language. Clustered to the left in Fig. 2, texts from the four familiar sources are similar to one another and to language used in the experiment during the first six trials. The right side shows that as teammates gain experience with one another in subsequent trials, message texts become more and more distinct from familiar text, i.e., specialized.

2.6. *Results 3: Drift away from function words*

Much of the change evident in Fig. 2 is due to teammates using fewer function words. Function words operate to connect content words in a sentence. Example function words are pronouns (he is a new victim), prepositions (go to the store), articles (a, the), and auxiliary verbs (verbs that indicate the tense, mood, or voice of other verbs, e.g., I would have gone). Function words are often described as the glue that holds a sentence together. Content words are sentence elements held together by function words. For example, nouns (he is a new victim), verbs (he is a new victim), and adjectives (he is a new victim) are content words.

Fig. 3 shows systematic drift away from function words as teammates become more experienced with one another. Function words are about half of the words in initial messages (52% in trial one), which is usual for text from the familiar sources in Fig. 2 (53% in blogs, 55% in novels, 46% in tweets, 42% in the New York Times). About half as many function words are used during the final trial (24%).[4]

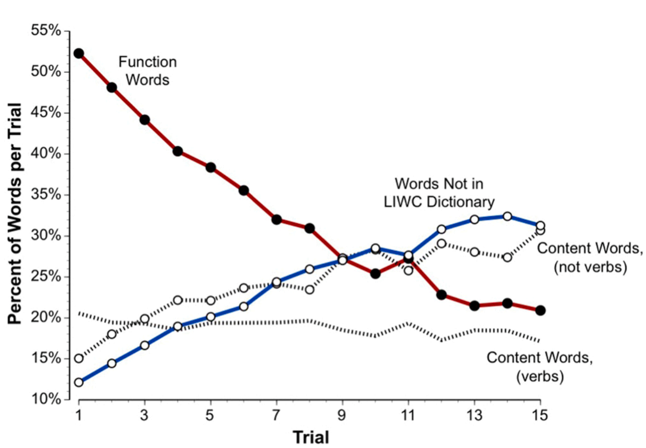


Fig. 3. Language Drifts Away from Function Words.

The drift away from function words presumes teammates understand one another without the linguistic connective tissue of function words, which raises a question: Prior work with LIWC profiles shows that people coordinate on function words (measured by a "Language Style Match" index, LSM, Gonzales et al., 2010). Coordination on function words has been reported to covary with successful negotiation (Taylor and Thomas, 2008; Bayram and Ta, 2018), CFO achievement (Shi et al., 2019), and social attachment in student teams (Gonzales et al., 2010; Ireland et al., 2011; Tausczik and Pennebaker, 2013; Kovacs and Kleinbaum, 2020). How can function words be a foundation for coordination if language shifts away from function words?

One answer would be that the aggregate drift is in fact a shift to a subset of function words. There is evidence of team leaders using more plural pronouns, as in "our plan," while less central teammates use more singular pronouns as in "my plan" (Kacewicz et al., 2013). It could be that as teammates become conscious of themselves as a team, there is a shift away from the full range of pronouns to the subset of plural pronouns more consistent with a team perspective such as "us," "we," and "our." This possibility seems unlikely since there is similar drift away from subcategories of function words (Fig. S4). Still, Fig. 3 shows that one in four words during the final trial are function words. One in four is much lower than the initial use of function words, but one in four is still a substantial use. Teammates could be coordinating on the few function words retained in team discussion. We wondered whether teammates align in their use of the function words they continue to use, and whether any individual teammates stand out as leading the drift away from function words.

We conclude there is no evidence of either, from which we infer that

[4] Two details on this result. First, the aggregate trend is evident in subcategories of function words (Figs. S3 and S4). Second, given the high proportion of function words in familiar text, and the obvious decline in Fig. 3, we wondered whether the LIWC "total function words" category is responsible for the text ordering in Fig. 2. Excluding function words, we computed distances across the other 72 LIWC categories, and re-ran the multidimensional scaling. Text positions on the resulting horizontal axis are correlated.99 with text positions on the horizontal axis in Fig. 2, so there is more going on than just change in the "total function words" category — in some part because the "pronoun," "auxiliary verb," and "articles" subcategories are prominent as function words and are similarly used less often by more experienced teams (see Fig. S3).

the drift away from function words is a by-product rather than a goal. Two results support our conclusion. First, no teammate stands out for leading or lagging in the drift away from function words (Fig. S5A). Second, teammates do not become more similar in use of the function words they continue to use. Rather, they become more different (Fig. S5B). We reach the same conclusion if we compare teammates for their relative use of kinds of function words (pp. 6–7 in online supplement).

2.7. Results 4: Convergence on jargon

The drift away from function words is a by-product of a drift toward content words. The four lines in Fig. 3 sum to 100%. A declining percent function words is balanced by a corresponding increase in percent content words. On average, messages during a team's first trial contain 35.5% content words, which increases to 47.8% by the 15th trial. Two dashed lines in Fig. 3 show that the increased use of content words is primarily words identifying people and things rather than actions. The dashed line for verb use in Fig. 3 is relatively consistent over time, from 20.5% in the first trial, to a similar 17.1% in the 15th trial. In contrast, the dashed line with hollow dots describing the use of content words other than verbs increases from 15.0% in the first trial, to 30.6% in the 15th trial.[5]

Use of unusual words increases by a similar amount. On average, 80% of all words exchanged during the experiment are captured by the LIWC dictionary, leaving 20% not in the dictionary. By dint of not being in the dictionary, we refer to such words as unusual; not odd, just not generic enough to be in the LIWC dictionary. The solid line with hollow dots in Fig. 3 shows how the use of unusual words varies with team experience. The LIWC dictionary cannot identify a little more than 10% of words in messages during the first trial. The initial percentage increases to 25% mid-way through the experiment, then to 32% in the final three trials. Unusual words here are often labels teammates use to identify the abstract symbols on which they coordinate; labels such as "angelmouse," "gheisha," "parallelogram," or "ymca." These understandable, but unusual, words are not in the LIWC dictionary. Of course, teammate messages were typed quickly and under pressure during the experiment. Typos were abundant and could create an illusion of unusual words since misspelled words are less likely to be in the LIWC dictionary. However, the LIWC profiles we analyze from raw text are similar to profiles created from text corrected for typos (Fig. S1).

For concrete illustration of language change with team experience, Table 1 lists the messages sent by a person during his first trial. There are 288 words in the subject's messages. About half are function words (53%): especially pronouns (e.g., I, we, he, she; 15% of the message words are pronouns), prepositions (e.g., from, to, with; 17% of the message words are prepositions), and auxiliary verbs (e.g., should, would, may be; 13% of the message words are auxiliary verbs). There is a great deal of confusion over the identity of the symbols in one another's hands, and the subject uses familiar language (as expected from Fig. 2). At the conclusion to this trial, the subject incorrectly identified the shared symbol, and three of his four teammates also got it wrong. Function words populate the Table 1 messages referring to who said what, subject intensions, and the descriptive identity of symbols — that is to say pronouns, prepositions, and auxiliary verbs.

In contrast, Table 2 lists messages sent by a subject during her team's 12th trial. Content words populate the messages, referring to action, and by mutually understood labels, to the symbols in a subject's hand — that is to say verbs and nouns. The subject begins by sending messages that

Table 1
Illustrative messages during first trial.

- "a figure that looks like its leg is out; a figure that looks like it's pointing; a figure with its arms out; a figure that look like it has long ears and is laying back, and a figure that looks like it's sitting back"
- "What about you?"
- "What are the symbols you have?"
- "1. looks like its leg is out in a kicking motion 2. one with arm or object out 3. one with arms out - "4. one laying back with long ears 5. one sitting down with knees up"
- "What symbols do you have"
- "Looks like we all may have kicking man"
- "Yes to kicking man, man kneeling, man sitting with legs out""
- "Looks like we all have kicking man as the 1st one"
- "Looks like we all have kicking man for the first one"
- "Left to right I thought"
- "Yes"
- "Got it"
- "Believe so"
- "1, 2, 5"
- "I think I'm gonna do that too"
- "Yes"
- "I went with kicking man"
- "I went with kicking man"
- "I went with kicking man"
- "Yes"
- "looks like x3 said he/she does as #1 from right"
- "What is your #1 on the left"
- "Do we all have to have the symbol in the same place? x3 has kicking man but as #5 from left to right"
- "yes"
- "I think so too but x5 is saying x3 doesn't have kicking man but x3 does just in different order"
- "should we go with knees bent then"
- "x5 is saying we all have man with knees bent"
- "yeah"
- "I'm gonna go with knees bent for the sake of time"
- "I would like to!"
- "let's do that one then so we can move on"
- "Yes! I've responded"
- "we may be trying to move on"

NOTE — These are all of one subject's messages sent during his first trial, listed in order of time sent ("x3″ and "x5″ refer to teammates)

Table 2
Illustrative messages in later trial.

- "walking left, arms up, kneeling, bunny, sitting left"
- "walking left, arms up, kneeling, bunny, sitting left"
- "walking left, arms up, kneeling, bunny, sitting left"
- "walking left, arms up, kneeling, bunny, sitting left"
- "sitting left"
- "sitting left"
- "sitting left"
- "sitting left"
- "yes"
- "submitted"

NOTE — These are all of a subject's messages sent during trial 12, listed in order of time sent.

list the symbols in her hand for that trial. Teammates exchange messages to determine that "sitting left" is the symbol they share, which the above subject confirms with "sitting left" messages to teammates. A "yes" message is exchanged with a friend, followed by a "submitted" message to confirm to the friend that the subject submitted "sitting left" as her best guess of their shared symbol. "Submitted" is the subject's final message during the trial. All five teammates in this trial correctly identified their shared symbol.

Of 42 words in the Table 2 messages, nine percent are function words (the preposition "up" is used four times). There are zero pronouns, and zero articles. Processed through LIWC, the words indicate relativity (walking, left, up, sitting), body/biology (arms, kneeling), and motion (walking). The team has assigned names to the abstract symbols from past trials so they can quickly identify in trial 12 the symbol they have in

[5] The category "content words (not verbs)" in Fig. 3 is not defined by the LIWC dictionary. We approximated the percentage of words in this category from the absence of the other three categories in Fig. 3, which are defined in the LIWC dictionary (i.e., content words (not verbs) = 100 − percent verbs − percent function words - percent words not in LIWC dictionary).

common. They could communicate more quickly with shorter labels such as A, B, C, or 1, 2, 3. Instead, the anthropomorphic names they use, such as "walking left," "arms up," "kneeling," "sitting left" — are intuitively descriptive and entertaining for the teammates, and therefore easy to remember (corresponding to the above quote from Weber and Camerer, 2003).

We refer to the task-critical, symbol-identifying terms in Table 2 as jargon. They are labels used jointly by teammates to identify and distinguish the abstract symbols on which teammates coordinate. The drift away from function words we attribute to indifference, not intention. The drift is a by-product of teammates shifting to jargon. With jargon indexing a volume of information familiar to an experienced teammate, messages can be simplified to content communicated explicitly. In Table 2, for example, all but two of the 42 message words are jargon. As a measure of the extent to which a text is jargon, we use percent jargon defined as 100 times the number of jargon words in a text divided by the total number of words in the text. A team has converged on jargon to the extent that jargon is a high percentage of the words in teammate messages. The text in Table 2 is 92.5% jargon (100 * [40/42]).

2.7.1. *Identifying jargon*

To identify jargon, we searched through a team's messages during the final trials (13, 14, and 15) for the last and shortest content phrase that teammates used to distinguish each symbol from the others. The identified phrase is treated as the team's jargon term for the symbol. If the words most often used in a team's final messages are not content words, we adopt as jargon the six content-word phrases most often used to identify symbols in the team's final trials.[6] To compare teams with equal opportunity to converge on jargon, we only identified jargon for the 48 teams that made it into the final three trials.[7] In most cases, jargon is a single word (75.7% of 288 terms for six symbols in 48 teams), but word pairs are also popular (20.5%). Jargon longer than two words is rare (3.8%).

The six symbols on which teammates coordinate are displayed in Fig. 4 with the jargon term most often used to identify the symbol, the percent of teams that adopted that term, and the number of other terms used to identify the symbol. For example, the symbol to the upper-right is most often referenced as "kicker," a term adopted in five teams (10% in Fig. 4). The other 43 teams used a total of 26 different terms to reference the symbol. Example jargon terms are listed below the symbol.

Jargon evolves as it is used, so the task of identifying a specific term as jargon necessarily involves an element of judgement. For example, "elephant" under the "kicker" symbol in Fig. 4 began as "looks like an elephant from the side," which became "dancing elephant," and ended up "elephant." The team that settled on "angelmouse" for the "kneeling" symbol used a variety of labels (selected messages are listed in Table S4 in the supplement). During the eighth trial, someone says the team needs to use consistent names. Someone figures out that what teammates have referenced as "angel" is the same symbol referenced by others as "triangle wings." Another teammate makes the connection with "mouse." The team exits trial eight with "triangle = angel = mouse," and one teammate grumbling that "it doesn't even look like a mouse," which earns him a command to "pick that one!" During the ninth through 15th trials, teammates use combinations of mouse and angel, finally converging on "angelmouse" during the 15th trial. Given the subjective element in the coding, we coded the final messages for jargon independently so we could report on coding reliability.[8]

As expected from the network-information premise, separate teams often adopt different jargon. Not every team is different on each symbol, but difference is more common than similarity. A total of 153 terms are adopted for the six symbols in 48 teams. The most frequently used is "bunny" for the symbol to the upper-left in Fig. 7. "Bunny" is adopted in 24 teams to reference the symbol, and the related term, "rabbit," is adopted in another 13 teams. "Bunny" is an exception. Of the 153 terms adopted as jargon, 114 are adopted by only team (74.5%). Looking through the illustrative jargon in Fig. 7 some stand out as inventive, such as "YMCA" and "wtf" for the upper-right symbol, "angelmouse" and "yoga" for the lower-left symbol, or "arm muscle" for the bunny symbol. Match between symbol and jargon can be more or less interesting, more or less obvious. Interesting or obvious are an aside to the critical issue of teammate agreement. "Gheisha" consistently used in one team for the lower-right symbol in Fig. 4 is consistently "geisha" in another team.

2.7.2. *Observed drift into jargon (Hypothesis 1)*

Fig. 5 shows the drift into jargon. The vertical axis is the percent of words that are jargon during trials grouped into periods of three trials. Consistent with Hypothesis 1, jargon becomes more prominent, on average, in messages as a team becomes more experienced. There is substantial variation between teams, but median percent jargon increases across the five periods from 5% to 14%, to 27, to 35, and to 46%. The increase across periods is statistically significant (25.46 coefficient for log period predicting percent jargon,.71 correlation, 15.43 t-test, $P < .001$), with each period-to-period advance statistically significant, especially following the initial trials (respective t-tests of 2.56, 9.32, 10.11, and 9.19 for each period compared to the former period).[9] Since more experienced teams are more efficient (Fig. 1), the drift into jargon is associated with the greater efficiency of experienced teams — as well as the relative extent to which a team becomes efficient: Teams that use more jargon in their final trials finish those trials more quickly (−1.24 coefficient for percent jargon predicting seconds per trial, −0.53 correlation, −4.26 t-test, $P < .001$).

The correlation matrix in Fig. 5 shows that the drift into jargon is more or less continuous. Teams that do well in converging on jargon during a period tend to be teams that did well in converging during the previous period. The matrix tell us three things about the process. First, the drift into jargon is not due to constant exogenous differences between teams, either in team ability or the network structures to which teams were assigned (discussed in the next section). The correlations are not uniformly high as if produced by a factor recurring in each period. The first principal component describes .66 of matrix variance, which shows stability, but not to a point expected of a constant factor. Second,

[6] This contingency is illustrated in the team to be discussed in association with Fig. 7C.

[7] The 48 study teams are comprised of 45 that completed all 15 trials, one that completed 14, and two that completed 13. Subjects in the 22 teams that collapsed before reaching the final trials expressed their frustration and irritation with the coordination task (Burt et al., 2021:39–40). Analysis of covariance corroborates the expressed emotions. Subjects in the collapsed teams worked harder and developed less than subjects in the 48 study teams. Fortunately for our interest in network correlates, team collapse is independent of the four network structures to which teams were assigned (2.30 chi-square, 3 d.f., $P \sim .51$).

[8] The two authors executed the task in slightly different ways, which warrants a note for future work. Distinguished as "literal" versus "figurative" coding strategies, we adopted the figurative strategy for the analysis because it is closer to our definition of jargon. Still, there is merit to comparing the two coding strategies to get a sense of reliability, so we provide details in the online supplement (see "Jargon Data" in the supplement). The key point for the analysis is that reliability is high on average (89%, Table S2), does not differ significantly across the six symbols (Table S3), and low reliability is concentrated in a few teams that least converged on jargon (Fig. S6). The higher the proportion of a team's final message words that are jargon, the more reliably the team jargon can be identified (Fig. S6, Table S3), which reinforces our decision to focus on jargon in the teams that made it into the final trials of the experiment.

[9] All tests in this sentence were computed using the Stata "cluster" option to adjust standard errors up for autocorrelation between repeated observations of each team.

Fig. 4. Tangram Jargon, NOTE — Tangrams are listed in order of increasing variation in jargon. Most common jargon for a symbol is listed under symbol with percent of teams using that jargon and number of other terms used as jargon. Rows below symbol list jargon words from diverse teams as illustration.

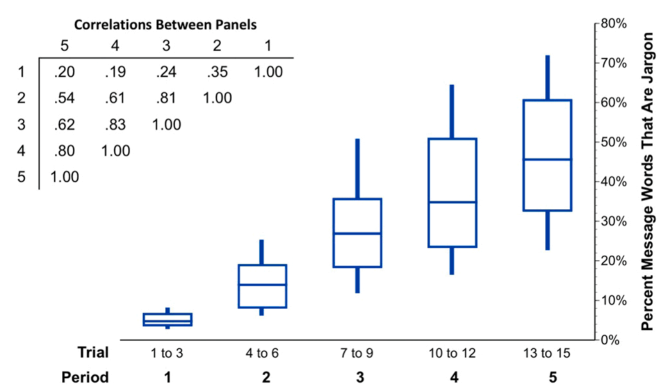


Fig. 5. With Experience, Messages Become Increasingly Composed of Jargon, NOTE — Box plots show 10th, 25th, 50th, 75th, and 90th percentiles within each period. Correlations are between percent jargon during time periods.

the endogenous drift into jargon is incremental. The matrix resembles a "simplex" structure with high correlations between percent jargon in adjacent periods, and decreasing correlations between periods further apart. Such a structure is to be expected if teams build during each period on what they learned in the previous period.[10] Third, to the extent that the drift into jargon is discontinuous, discontinuity occurs during the third period. The second principal component (0.19 of matrix variance) distinguishes percent jargon in periods 1 and 2 from percent jargon in later periods. We take advantage of this partition below when we use network pulse to predict jargon.

[10] Rogosa and Willett (1985) offer a didactic discussion of inferences about simplex structure in correlation matrices, highlighting a guideline from three decades before: A structure is simplex if partial correlations between nonadjacent periods are zero when the intervening period is held constant. In Fig. 5, the.61 correlation between periods 2 and 4 is a statistically negligible partial correlation holding period 3 constant (P ~.21). Similarly, the correlation between periods 1 and 3 is negligible when period 2 is held constant, and the correlation between periods 3 and 5 is negligible when period 4 is held constant (P ~.32 and.62 respectively). Thus we say the matrix resembles a simplex structure.

3. Network structure behind the drift into jargon

Past research leads us to expect that the social network among teammates affects the drift into jargon. We begin with network structure as the received wisdom, then turn to network pulse.

3.1. The centrality hypothesis

Received wisdom about network structure and team performance is organized around a contrast between two images. At one extreme is a team composed of leader and subordinates. Like a mainframe computer connected with dumb terminals, communication is between leader and each subordinate, with the leader coordinating the work of the subordinates. At the other extreme is a group of colleagues communicating with each other. Like parallel processing across connected computers, communication and leadership are distributed across teammates. In network terms, the first extreme is centralized, often termed a WHEEL network, in which the leader is a hub from which spokes link the leader with each subordinate. Various terms are used for the other extreme, but we will use the graph theoretic term of a CLIQUE network in which every element is linked with every other element. The contrast between CLIQUE and WHEEL is measured by a variety of alternative network indices anchored on the idea of relations concentrated in a single teammate, which measures a team's similarity to a WHEEL (Freeman, 1978, reviews early measures).

We will refer to the received wisdom about team network and performance as a "centrality hypothesis" in deference to its origins in the Bavelas-Leavitt-Smith experiment. The team coordination task was made simple to highlight network effects. The task was to identify which of the following symbols teammates held in common: ○ △ ◇ □ + ✱. As described in a report on the project (Christie et al., 1952:29): "Our aim in every case was to devise the task so that the intelligence or speed of reasoning of any individual in the group would not be a limiting factor in the performance of the group. A general feature of all the experimental tasks has been that an individual, substituted for the group, would have found the task trivial." There is no record of messages sent in the early experiments, but it seems safe to presume that teams did not resort to jargon since the above symbols are familiar in every-day speech: circle, triangle, diamond, square, plus, and asterisk.

Leadership can speed coordination on such a task, as was demonstrated by the faster, more accurate work performed by teams assigned to a WHEEL network (e.g., Leavitt, 1951; Guetzkow and Simon, 1955; Cohen et al., 1961). The WHEEL network was argued to be a productive limitation on independent behavior from teammates. Leavitt (1951:50) summarized: "centrality affects behavior via the limits that centrality imposes upon independent action. Independence of action, relative to other members of the group is, in turn, held to be the primary determinant of the definition of who shall take the leadership role, total activity, satisfaction with one's lot, and other specific behaviors. More precisely, it is felt that where centrality and, hence, independence are evenly distributed, there will be no leader, many errors, high activity, slow organization, and high satisfaction." In a later replication, Cohen et al. (1961:428) offer a summary more keyed to management: "The more a leader is clearly recognized and agreed upon …, the more likely will other members accept influence attempts by him: procedures, answers, etc. Less energy and time will be spent by other members in duplicating the functions of the leader: figuring out answers for themselves, checking on others (once the leader has approved information by passing it on), and trying to set up variations in problem-solving procedures according to their own idiosyncratic evaluations."[11]

Variations on the original experiment using complex tasks quickly followed. The variations showed that teams assigned to a WHEEL network do not master complex tasks as quickly as teams assigned to more densely connected networks. A popular option was to ask subjects to coordinate on a logistics problem (e.g., Shaw, 1954, for illustration, Burgess, (1968:325), for a list of studies). More relevant to jargon is an unpublished study by Sidney Smith, the person who designed the original Leavitt experiment run in 1948. In 1950, Smith ran what he termed a "noisy marble" variation of the original experiment (Christie et al., 1952:136-171). The task was to identify which one of six marbles the five teammates have in common. The initial 15 trials were simple in that the six marbles could be unambiguously identified by solid color (red, blue, black, yellow, green, and white). The subsequent 15 trials were complex in that the marbles differed by (Christie et al., 1952:136-137): "cloudy, mottled, indistinct colors. They were still easy to distinguish if they could be directly compared, but it was very difficult to describe each one clearly and unambiguously." In other words, subjects had to coordinate on words to identify the marbles in order to determine which marble they held in common. On the initial trials with unambiguous marbles, teams assigned to a WHEEL network perform as well as teams assigned to more connected networks. In the subsequent trials with "noisy marbles," teams assigned to a WHEEL network perform poorly (Christie et al., 1952:140-141, especially figures V.1 and V.5).

Failure was attributed to a lack of access between teammates in a WHEEL network (Christie et al., 1952:153): "The two effects which seem to be of importance here are the lack of a sense of participation on the part of the peripheral men and their ignorance of the confusion which their ambiguous descriptions cause. Consequently, messages from the central node asking for better descriptions are not effective because the peripheral men have no chance to know the deficiencies of their original descriptions, and do not realize the number of errors which are actually occurring, since they see only a small part of the process." The successful performance of teams assigned to more connected networks was attributed to more complete information (Christie et al., 1952:153): "In the circle groups, on the other hand, the work of deciding on the answer is shared more or less equally among the subjects, and messages flow freely around the network; hence, they soon realize both the extent and the source of the confusion and are more easily able to correct it by a joint attempt to clarify their descriptions."

In sum, the centrality hypothesis is that communication concentrated in a single teammate enhances team coordination on simple tasks by limiting independent behavior from teammates, and for the same reason inhibits coordination on complex tasks. The centrality hypothesis is generally supported in contemporary research. Park et al. (2020) offer review, and Balkundi et al. (2019) offer review focused on network brokers within and across teams. Balkundi and Harrison (2006:49), corroborate the hypothesis with a meta-analysis of 37 studies of teams in natural contexts, concluding: "teams with densely configured

[11] These quotes emphasize the clarity of leadership defined by network centrality. Teammate agreement on perceived leadership is the dependent variable in Burt et al. (2021) analysis of the renovated experiment, so we have it well measured. While perceived leadership is correlated in the expected way with network structure, it is uncorrelated with team convergence on jargon, so we do not discuss it in the paper. We have no evidence to believe that the lack of jargon in centralized networks is due to teammates consciously reacting to, or resenting, the concentration of messages in one teammate. Details are in the online supplement.

interpersonal ties attain their goals better and are more committed to staying together; that is, team task performance and viability are both higher."

Here are a few illustrative studies: Sparrowe et al. (2001) use survey network data on 38 teams in five organizations to measure the extent to which advice relations are concentrated in a single teammate and difficult relations are common between teammates. Consistent with the centrality hypothesis, there is a slight tendency for teams to receive higher team leader evaluations when relations are less concentrated in a single teammate, and a discernable tendency for low team evaluations when teammates have widespread difficulty with one another (respectively, P ~.06 for "advice centralization" and P ~.01 for "hinderance density," Sparrowe et al., (2001:322). Cummings and Cross (2003) use survey network data on 182 work groups across a global organization to measure the extent to which discussion during the team's work was concentrated in a single teammate. Consistent with the centrality hypothesis, there is a strong tendency for teams to receive higher evaluations from the manager above the team when relations are less concentrated in a single teammate (P < .001 for "hierarchy," Cummings and Cross, 2003:206). Carson et al. (2007) use survey network data on 59 consulting groups of MBA students to measure the density of relations in which teammates see one another as providing team leadership. Consistent with the centrality hypothesis, there is a strong tendency for teams to receive higher client evaluations when perceived leadership is distributed across teammates (r = 0.46, t = 3.81, P ~.001, Carson et al., (2007:1227). In an unusual exercise, Parise and Rollag (2010) use survey network data to measure network density before and after students are randomly assigned into 42 teams. Density is a reverse measure of centralization; the higher the density, the lower the concentration of relations in one teammate. Consistent with the centrality hypothesis, there is a strong positive association between density and team performance in terms of correctly completed tasks. Above and beyond the positive performance association with network density during the exercise, there is a strong positive association with prior network density (Model 4, standard errors not presented, Parise and Rollag, (2010:891). Grund (2012) uses two years of game data on 73 soccer teams to compute network centralization within a team from the extent to which passing is concentrated in a single teammate. Consistent with the centrality hypothesis, there is a modest tendency for teams to score more goals when passing is less concentrated in a single player (P ~.05, Grund, 2012:687).

Given that direct communication between teammates facilitates team coordination on complex tasks (centrality hypothesis), and given that jargon enables people to quickly and accurately process complex information, we expect that teams are less likely to drift into jargon when communication is more concentrated in a single teammate:

Hypothesis 2. Jargon is less likely to emerge in teams wherein communication is concentrated in a single teammate.

3.2. Results 1: Random assignment to network structure

Initial results offer modest support for the hypothesis. Fig. 6 shows the distribution of percent jargon for teams assigned to each of four network structures defined in the experiment. Subjects are assigned at random to seven positions in the networks. All communication between teammates is through a computer keyboard so network structure is imposed on a team by restricting messaging as indicated by the lines in the sociograms.

Fig. 6 displays assigned networks in order of communication concentration in a single teammate. The baseline is a CLIQUE network in which every teammate can communicate with every other teammate. Of the 10 communication channels in the network, every teammate is involved in four, so 40% of team communication is concentrated in any one teammate. The opposite extreme is a WHEEL network in which a team leader coordinates the activities of all four teammates as subordinates. One hundred percent of communication in a WHEEL network is with the subject assigned to the hub of the wheel. The other two assigned networks are less centralized variations on the WHEEL. The Disconnected Brokers (DB) network has two leaders independently coordinating the activity of three shared subordinates (either leader is involved in 50% of team communication). The Connected Brokers (CB) network is a DB network in which the two leaders communicate directly (either leader is involved in 57% of team communication). The CB network can also be discussed as three overlapping cliques, each containing the two leaders plus one shared subordinate.

Consistent with Hypothesis 2, percent jargon in a team's messages during the final trials is lower when communication channels are concentrated in a single teammate (−0.24 regression coefficient predicting percent jargon from communication concentration, −0.32 correlation, 2.27 t-test, P ~.03). But percent jargon varies widely between teams assigned to the same network. The within-network variation is such that differences between the four assigned networks are statistically negligible (2.37 $F_{(3,44)}$, P ~.08), with the one exception that percent jargon is noticeably low in teams assigned to a WHEEL network. Teams assigned to a WHEEL network average 36.3% jargon in their final trials, versus 49.5% jargon in teams assigned to any of the other three networks (−2.22 test statistic for WHEEL, P ~.03). Percent jargon in teams assigned to the two intermediate networks is indistinguishable from percent jargon in teams assigned to a CLIQUE network ($F_{(2,32)}$ = 0.86, P ~.43).

3.3. Assigned versus behavioral network structure

We dug into outlier teams to better understand the jargon-network association. Three teams are labeled in Fig. 6: Two extremes among teams assigned to a CLIQUE network, and one team among those assigned to a WHEEL network. Fig. 7 displays word-cloud images of messages within each of the three teams during the initial and final trials of the experiment. Larger text indicates more frequent use.

The team in Fig. 7A is a model of efficiency. The team was assigned to a CLIQUE network, so it is expected under Hypothesis 2 to do well with the complex task of coordinating on labels for the six abstract symbols. Boxes below the word clouds in Fig. 7A show learning in fewer messages required to complete the task (117.35 per trial initially, down to 28.7 per final trial), and faster task completion (4.1 min per trial initially, less than a minute for the final trials). Across trials, as teammates become more experienced with one another, they require fewer messages to complete their task (number of messages in a trial is correlated −0.84 with log trial, Fig. 1). There is an accompanying change in language. The complexity of function and content words in initial messages (left word cloud) evolves into the use of primarily six words during the final trials: bunny, sitting, leg, gift, arms, skirt (right word cloud, first row of example jargon in Fig. 4). Those six words are the jargon teammates use to refer to the six abstract symbols. Once the teammates had the six jargon words, they did not need function words to perform their coordination task. They could directly coordinate by just naming symbols. For this team, function words drop from 45.5% in initial trials to 5.2% in final trials, and word use becomes concentrated in jargon: 86.8% of the words in their messages during the final trials are one of the six jargon words created by the team.

The team in Fig. 7B varies from Hypothesis 2 in that the team does almost as well as the team in 7A, despite the fact that the 7B team was assigned to a WHEEL network. The team goes down a steep learning curve (number of messages during a trial is correlated −0.84 with log trial). The team's 45.5% function words in messages during the initial trials drops to 14.6% in the final trials, and those messages during the final trials are 48.0% jargon words (second row of example jargon in Fig. 4).

The team in Fig. 7C sharply contradicts the network effect predicted by Hypothesis 2. The team was assigned to a CLIQUE network, but is markedly unsuccessful in the sense that teammates are often inaccurate

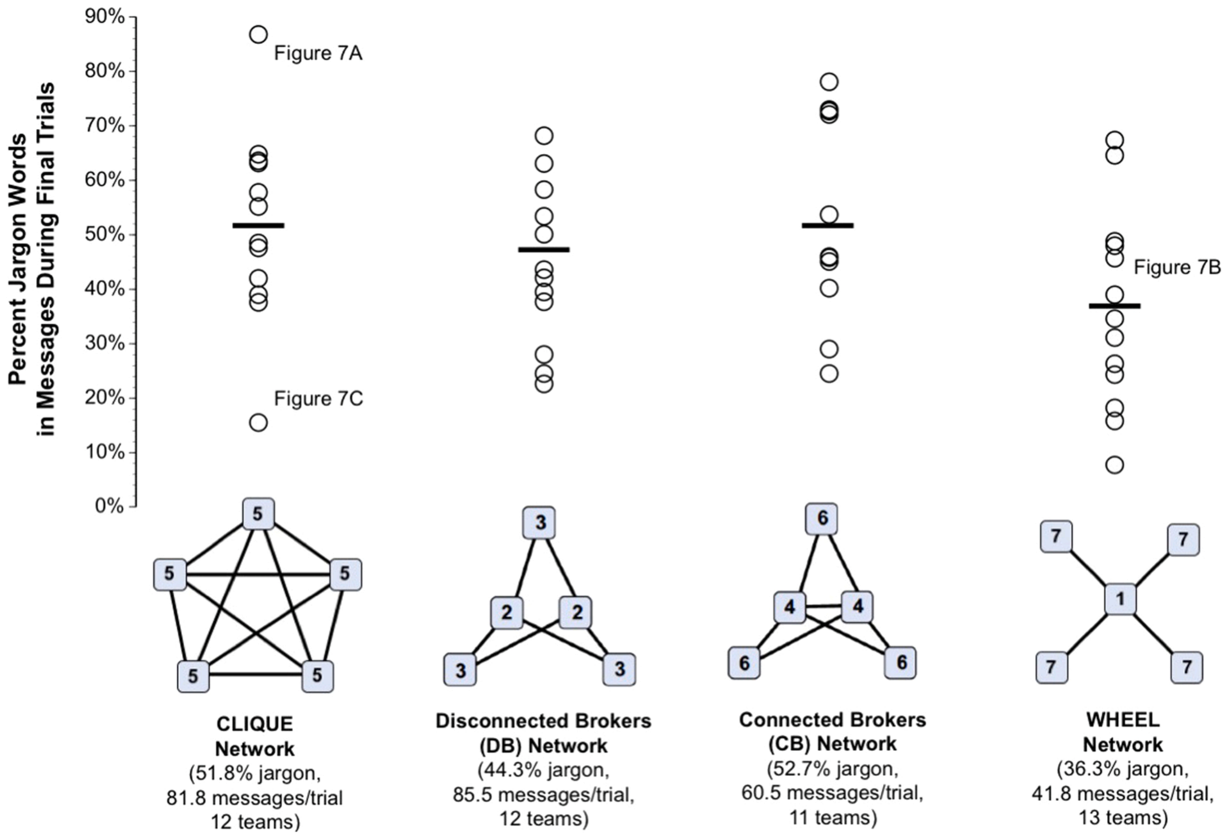


Fig. 6. Percent Jargon by Assigned Network, NOTE — Percent jargon during final trials (13, 14, 15). Horizontal bars indicate median jargon use within each team network. Words used in the initial and final trials for the four labeled teams are given in the indicated figures. Numbers in the network sociograms indicate seven positions in the assigned networks. Parentheses contain mean percent jargon, mean team messages per trial during the final trials, and number of teams averaged. The four assigned networks are presented in order of increasing concentration in a single teammate (respectively 40%, 50%, 57%, and 100%).

(33.3% accurate in final trials), and display the least learning of any team (−0.25 correlation between messages sent during a trial and log trial). For this team, function words are about equally frequent in their initial and final trials (55.7% initially, 46.3% in final trials), and little jargon is used in their messages during the final trials (15.5%). The words most often used in this team's final messages are not content words, so we followed the protocol of adopting as jargon the six content-word phrases most often used to identify symbols in the team's final trials. The words they most often used in the final trials are: have, the, one, I, do, it. All but "one" are function words. The closest the team came to shared content words as jargon are (in order of the Fig. 4 symbols): "arm muscle," "laying down," "elephant," "diamond head," "slanted person," and "big triangle," which together are in frequency 15.5% of all words in their messages during the final trials. If the Fig. 7C team were removed from the data, there would be a more pronounced difference in jargon use between teams assigned to CLIQUE networks. What went wrong?

The team in Fig. 7C seems to have been highjacked during the experiment. One teammate was so active in sending messages, and keeping teammates busy responding, that he (intentionally or not) converted the assigned CLIQUE network into a WHEEL. (We do not know the gender of the people in the experiment. We use "he" here to simplify later reference to the behavioral leader in this network.) The difference in activity is illustrated in Fig. 8 by sociograms in which more messages are indicated by thicker lines. Lines vary within each team, showing that some teammates communicate more often with one another, but the Fig. 7C team shows messaging much more concentrated in the teammate to the east. All lines with that teammate are thick. Lines not with him are thin. If we were to code the Fig. 7C team as having a WHEEL network, which it surely has in terms of behavior, then the team's failure to converge on jargon would be precisely what Hypothesis 2 predicts.

Where "assigned network structure" is one of the four networks in Fig. 6 to which subjects are randomly assigned, "behavioral network structure" is the network enacted during the experiment. Assigned network structure enjoys the privilege of being exogenous, legitimating research claims about cause and effect. But the network structure that affects outcomes is the behavioral structure in which subjects operate during the experiment, which is the structure relevant to testing network effects on team performance. Grund (2021):683), quite rightly highlights as an advance over prior work his use of interaction frequency during a match to measure network structure when predicting team performance. The general advice is to measure subject networks before network experiments so variation in prior learned network behavior can be held constant in the later analysis. That control is not available for the experiment analyzed here (which is common in network experiments). We proceed with behavioral network structure to better see the jargon association with structure, mindful that in so doing we lose some advantages of random assignment.

3.4. Results 2: Behavioral network structure

To capture centralized behavioral network structure, we measure the extent to which messages are concentrated in one teammate. For each teammate, sum the number of messages he sent with a sum of the number of messages he received, and divide the total by the number of messages sent by all teammates. The maximum ratio for a team then measures the extent to which messages in that team are concentrated in one teammate. We multiply the ratio by 100 to discuss concentration as a percent of messages concentrated in one teammate.

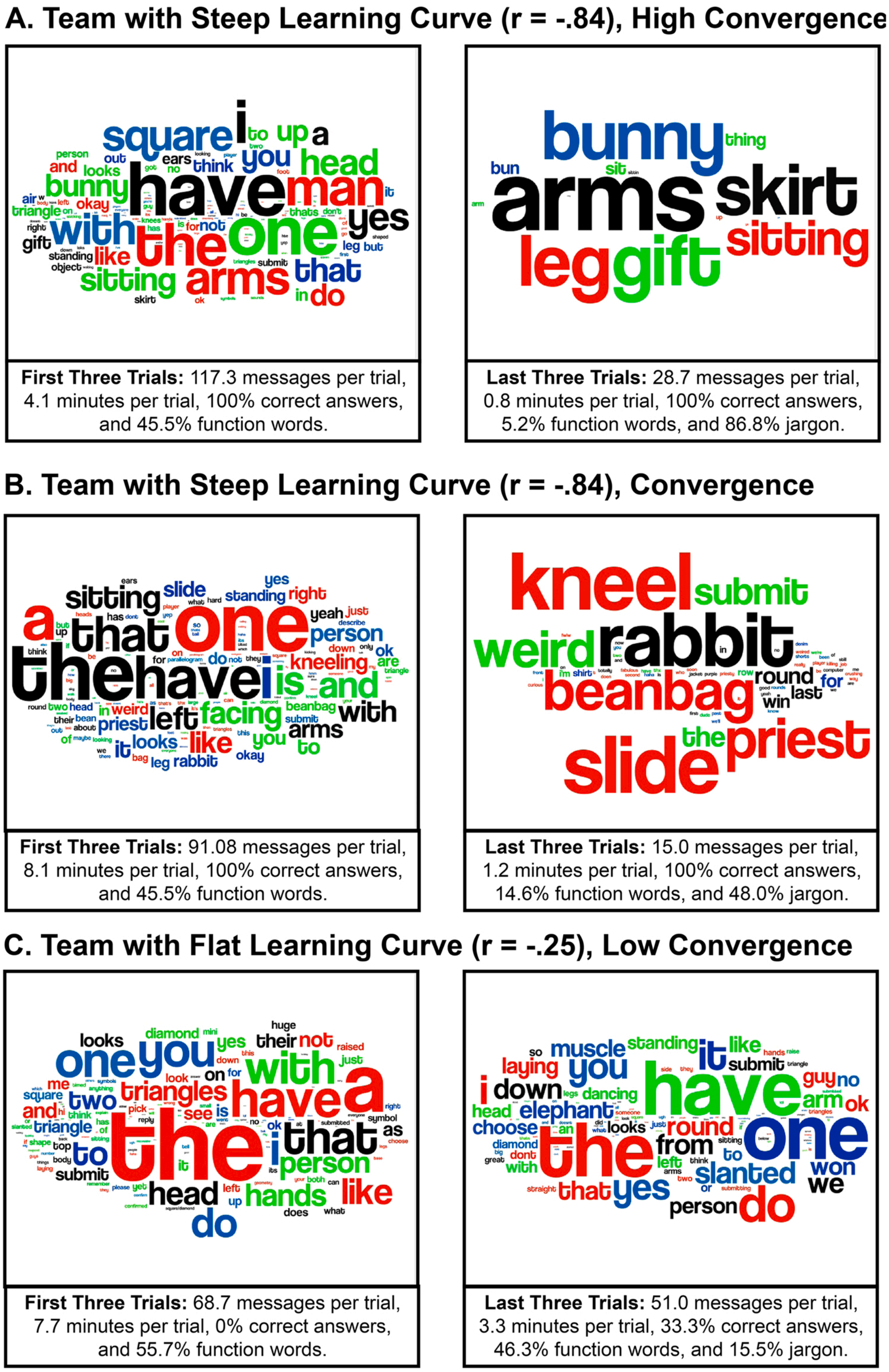


Fig. 7. Word Clouds for Messages During the Initial versus Final Trials in Three Teams, NOTE — Learning curve correlation in parentheses is between number of messages per trial and ln(trial). Averages across trials are given in box below word cloud.

Predicting jargon from behavioral structure improves the network prediction. Assigned network structure in Fig. 6 showed average jargon use during the final trials 13 points lower in teams assigned to WHEEL networks (36.3% versus 49.5%). A dummy variable distinguishing WHEEL networks predicts 11% of variance across the 48 teams in percent jargon. Message concentration in the assigned networks is about as predictive (0.10 R^2 using the concentration scores in the note to Fig. 6). In comparison, behavioral network structure in Fig. 9 shows a more consistent decrease in percent jargon. Predicted team variance in percent jargon is double what it was in Fig. 6 (R^2 = .25; −3.28 t-test, P ~.002). We separate WHEEL networks because there can be no variation in message concentration within teams assigned to WHEEL networks. With WHEEL networks included, however, the estimated behavioral network effect still soundly rejects the null hypothesis (R^2 = .21;

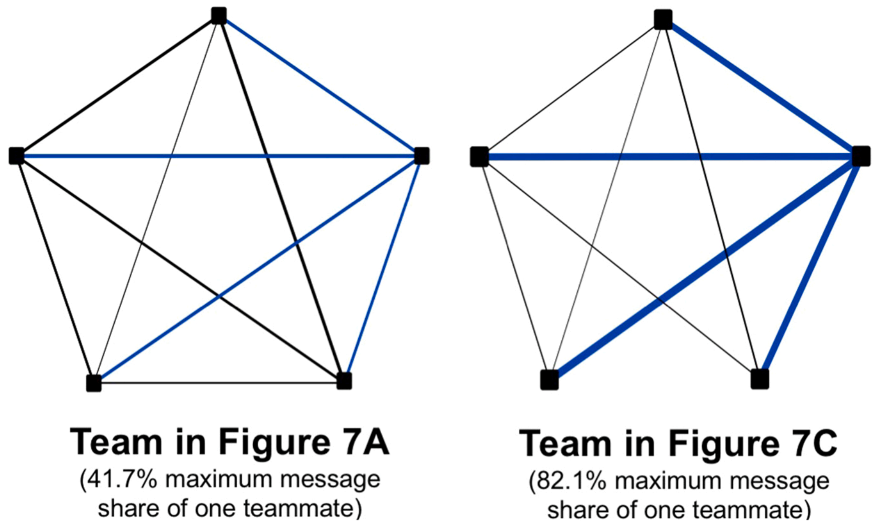


Fig. 8. Two Outlier Teams Assigned to CLIQUE Networks.

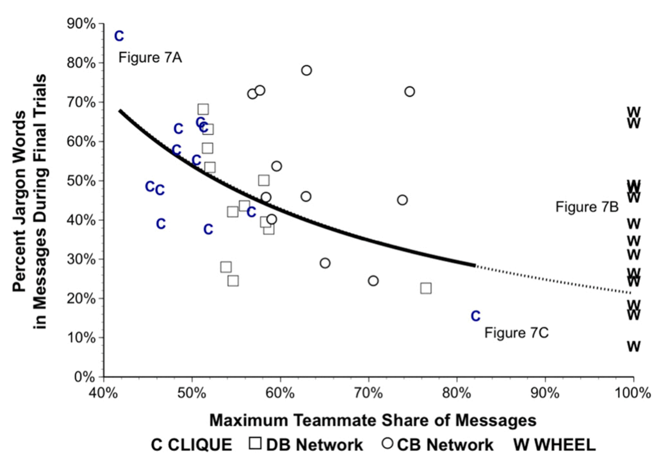


Fig. 9. More Centralized Network, Lower Percent Jargon, NOTE — Percent jargon during final trials (13, 14, 15) in 48 teams sorted on the horizontal axis by the concentration of messages in one teammate. Dashed line is extrapolation from solid line regression (footnote 12).

−3.50 t-test, P ∼.001).[12]

We can now highlight two qualifications that mitigate the loss of network random assignment when we switch from assigned to behavioral structure. First, the assigned networks are not equally open to bias from pre-experiment learned network behavior. The more relationship options subjects are given, the more that network behavior during the experiment can reflect pre-experiment learned network behavior. Variable exposure to pre-experiment learned network behavior is illustrated by variation in behavioral concentration within categories of assigned networks. There is zero variation within teams assigned to a WHEEL network. Every message within a team assigned to a WHEEL network is to or from the leader. There is some variation in message concentration within the two intermediate networks: 8.04 standard deviation in message concentration for teams assigned to a DB network, 7.75 for teams assigned to a CB network. The widest variation occurs in the assigned network that gives subjects the most choices: 11.80 standard deviation in message concentration for teams assigned to a CLIQUE network. If every subject in a CLIQUE exchanged the same number of messages with each teammate, message concentration for the team would be 40% (each subject would send 20% of team messages and receive 20%). In fact, message concentration within CLIQUE teams varies from 42% to 82% around a mean of 52%, with the teams at the extreme levels of message concentration displayed in Fig. 8. It was rare for communication to be equally distributed among teammates in a CLIQUE.

The second mitigating qualification is that message concentration is stable across trials in the experiment — which implies that the predictor is open to bias from pre-experiment learned network behavior, but little affected by variation in the dependent variable, percent jargon. Looking at the 48 teams across all trials, variation in message concentration is 98.8% between teams, only 5.2% within teams (Table S5 at the end of the online supplement). We constructed a matrix of correlations between average message concentration during each of the five periods in the experiment, like the correlation matrix in Fig. 5 for percent jargon. Message-concentration correlations are all between.97 and.98. The first principal component from the matrix describes 98% of variation in the matrix. The stability across trials is evident even if we put aside teams assigned to the WHEEL network, whereupon the first principal component still describes 88% of variation in the matrix.

4. Drift into jargon driven by network pulse

Network structure refers to pattern in the strength of relationships in a network, where strength varies with how long two people have known one another, how often they speak to one another, or how emotionally close they are to one another. Contact frequency is typically measured in broad units of time. For example, the General Social Survey name interpreter asks respondents to distinguish contacts met almost every day, at least once a week, at least once a month, or less than once a month (GSS variable "TALKTO"). These broad distinctions make sense for a study of relations that vary between daily and rare.

But when people assemble to discuss something, exchange is defined by more narrow time intervals. At one extreme, for example, is class discussion in which one student says something followed by a quiet moment before another speaks; or even worse, when the room just stares at you, no one knowing what to say. At the other extreme is class discussion in which students compete to speak their opinion, competing

[12] The regression line in Fig. 9 is a power function: $Y = aX^b$, estimated by OLS as $\log(y) = \log(a) + b\log(X)$, yielding estimates of 8.85 for intercept a and −1.24 for slope b. We prefer a simpler linear prediction, and a linear slope estimate rejects the null (−2.66 t-test), but fit to the data is noticeably worse (0.25 R^2 for power function,.18 for linear function). The dashed line extrapolation in Fig. 9 is the solid-line power function extrapolated to the maximum value on the horizontal axis. The percent jargon association with concentration in the assigned networks is the same with power or linear function (R^2 for both is.10).

with one another to be the louder voice heard, beginning to speak before another has finished. In colloquial terms, the latter would be described as "animated discussion." In network terms, we propose to distinguish it in terms of "network pulse." The pulse of a network refers to the rate at which messages are sent. The more crowded in time the messages, the higher the pulse. The above active class discussion has high pulse. The less active has low pulse. In one draft of this manuscript, we discussed message rate as the "velocity" of a network, but a velocity metaphor is not apt. Messages in our teams are transmitted instantaneously. Team differences occur in the rate of message fire, not the speed at which messages travel. We therefore settled on the biological metaphor of "pulse."

We were drawn to the rate at which teammates communicate by the pattern of jargon use across experiment trials. First, teams do not create jargon so much as they discontinue use of non-jargon (see "selective retention" section in the online supplement). Second, convergence on jargon is usually — not always, but usually — an evolution toward shorter phrases. In general, word frequency can be argued to result in word brevity (Zipf, 1936:28-29), but jargon is particularly prone to brevity. Jargon's purpose is to covey much using little. We mentioned in the discussion of Fig. 4 the sequence of "looks like an elephant from the side" reducing to "dancing elephant," then to "elephant." Krauss and Weinheimer (1964:114), cite the illustrative sequence of "upside-down martini glass in a wire stand," reducing to "inverted martini glass," then to "martini glass," then to "martini." Weber and Camerer (2003:408), cite the example of an office picture referenced in final trials as "PowerPoint" being initially identified by the text: "The one with three people: two men and one woman. The woman is sitting on the left. They're all looking at two computers that look like they have some PowerPoint graphs or charts. The two men are wearing ties and the woman has short, blond hair. One guy is pointing at one of the charts."

Jargon emerging through the discontinuation of non-jargon, and jargon's drift toward brevity led us to believe that time pressure is a factor in team convergence on jargon. The more frequently a teammate has to provide sensible responses to colleague questions, the greater the teammate's incentive to shorten responses that preserve content. Here are some illustrative motivational messages sent to teammates, each in a different team: "okay just submit it," "just submit," "lol I don't care if it's right or wrong I want people to just submit," "let's hurry up," "hey u fuck," "tell that person to hurry it up," "tell those morons to hurry the hell up," "do you enjoy just being a total dickhead." Over time, teammates learned to signal information quickly. To capture this time pressure on teammates to engage in jargon, we propose a pulse hypothesis:

Hypothesis 3. The higher the message rate within a team, the more likely the team converges on jargon.

Of course, the rate at which communication happens can be discussed as an element of network structure. Message rate is a measure of tie strength at a moment in time. For example, under the assumption that "a work relationship can be expected to vary depending on whether colleagues interact occasionally or all the time", Grund (2012:683,685); measures "network intensity" as the number of passes made between teammates on a soccer team while the team has the ball.

But the network mechanism for pulse is distinct from the one for centrality, so we prefer to break pulse out as a separate dimension in theory. Network structure is about who has access to whom. Lack of access in the form of communication concentrated in a single teammate is known for its negative effect on performing complex tasks, as illustrated by the association in Fig. 9. Any structure providing less than open access between teammates limits opportunities to learn about data held by the rest of the team, which limits teammate coordination. In contrast, network pulse is about motivation. Having to deal with many communications in a short interval of time creates an incentive to find a short cut to accurately communicate quickly — and improve upon it once discovered. Regardless of overlap between structure and pulse in terms of learning and access to information, the mechanisms by which they affect behavior are distinct. It is one thing to have limited opportunities to learn, quite another to have no incentive to learn.

4.1. Measuring network pulse

We measure the network pulse of person i during trial t in terms of messages per minute: m_i / T, where m_i is the number of messages individual i sends during the trial, and T is the length of time in minutes that the individual's team spends on the trial. The corresponding network pulse for the team is messages per minute sent by any member of the team, $(\Sigma_i m_i) / T$, where i runs across the five teammates. The two rates are linked in that the team rate equals the sum of the teammate rates. We focus on the team rate since our jargon measure is at the team level.

The pulse association with jargon is illustrated in Fig. 10. The graphs show message timing within three teams during the first trial. Time runs from left to right in seconds. Each dot indicates a message sent. A dot's location on the horizontal axis shows when the message was sent. The dot's row shows the teammate who sent the message. Teammates are numbered from 1 for most active to 5 for least active. The three teams in Fig. 10 correspond to the teams whose message content is described in Fig. 7.

The team in Fig. 10A sent a total of 159 messages during the 361 s they spent in their first trial, a message rate of 26.40 per minute. The dense distribution of dots in the graph, and the relatively high message rates for each individual teammate, show that the team had a high pulse of communication right from their initial trial. Consistent with Hypothesis 3, this team is the one in Fig. 7A that comes down a steep learning curve and converges almost exclusively on jargon.

The team in Fig. 10C sent a total of 66 messages during the 432 s they spent in their first trial, a message rate of 9.17 per minute. The team message rate is low (−1.28 z-score). Although the team is assigned to a CLIQUE network in which every teammate has access to everyone else, messaging is dominated by one person, who peppers his colleagues with questions before they can respond (teammate 1 has a 6.53 message rate during the trial). Scattered messages from the four teammates indicate their disengagement (0.66 mean message rate, which is about two messages every three minutes, which leaves a lot of idle time). This is the team in Fig. 7C that failed to converge on jargon.[13]

The team in Fig. 10B is the surprisingly successful Fig. 7B team assigned to a WHEEL network. The teammates all submit correct answers in the early and late trials, and converge to 48.0% jargon during the final trials. The subordinates (teammates 2 through 5 in the graph) are sending more messages than the subjects forced to be subordinates in Fig. 10C, but the overall message rate is about average for teams assigned to a WHEEL network (10.73 message rate for this team versus the 11.79 average for WHEEL teams). What distinguishes the team in Fig. 10 is their work ethic. The other two teams in Fig. 10 spend six and seven minutes on their first trial. The team in Fig. 10B spends more than

[13] Delays between messages are noteworthy. Delays can be analyzed for bursts of activity (small delays between messages are frequent, long delays infrequent, so bursts of interaction can be identified as a heavy-tail Poisson distribution in which long delays occur more often than expected, Barabasi, 2005), or analyzed for performance improved by coordinated bursts within a team (Saavedra et al., 2011, on "synchronicity"). Or delays can be put aside as "bench time" when a teammate is off the playing field. For example, subject 5 in the Fig. 10C network sent two messages during the first trial, within a 55 s interval, which would be a relatively fast message rate of 2.18 messages per minute for the interval when subject 5 is engaged. With respect to jargon, however, delay is a resting period, and we are interested in rate as a measure of time pressure encouraging jargon. Therefore, we include delays in the rate calculation to adjust rates down for subjects with delays between messages. According to Hypothesis 3, subject 5's inactive periods lessen his incentive to engage in jargon. Over the 432 s the team spends in their first trial, subject 5 has a slow message rate of 2 messages in 432 s, or 0.28 messages per minute.

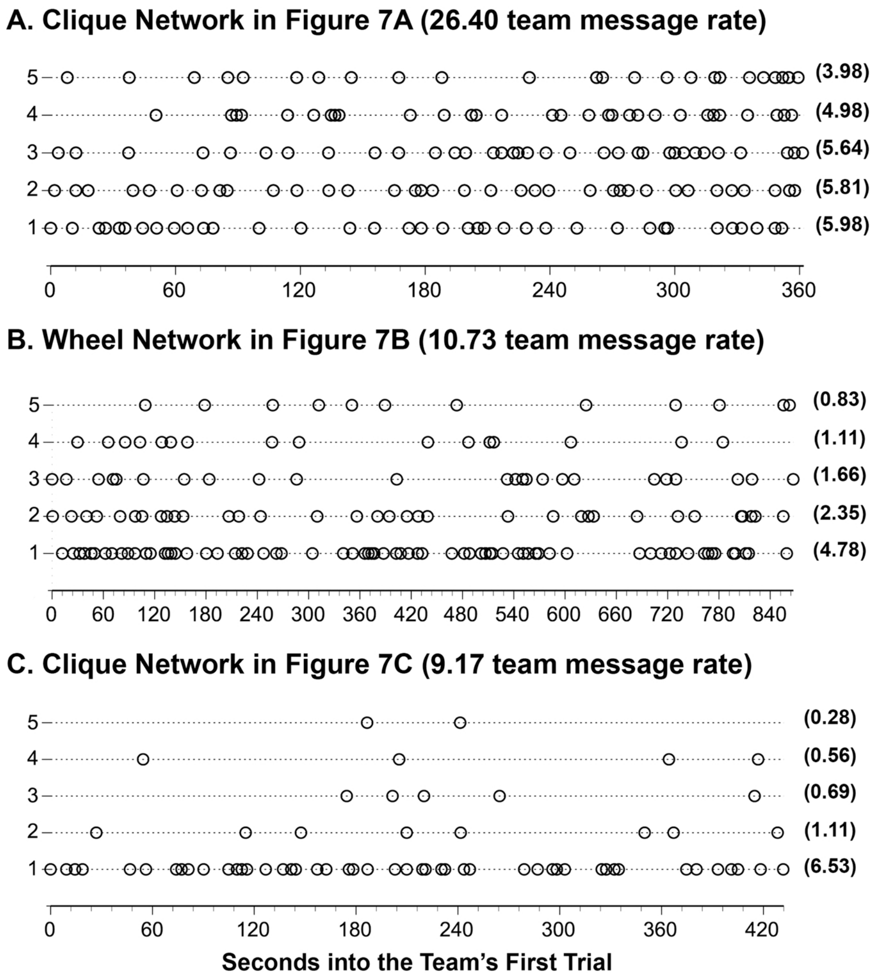


Fig. 10. Message Timing, Each dot is a message sent by the row teammate at a time indicated on the horizontal axis in seconds. The graphs show message activity during the first trial for the three teams in Fig. 7. Teammates are listed within teams from least to most active. Message rate is number of team messages per minute (individual teammate rates given in parentheses to the right of each row). Message concentration is the maximum percent of team messages in which one specific teammate is involved. Teams A, B, C spend 361, 867, and 432 s respectively in their first trial.

twice that (14.5 min,1.51 z-score among WHEEL teams in their first trial).

4.2. Results on network pulse

Teams are more clearly distributed along the regression line in Fig. 11 than was the case in Fig. 9 (behavioral network structure) or Fig. 6 (assigned network structure). A team's average message rate during early trials is used to predict the team's percent jargon in the final trials. A team that increases its message rate by one additional message per minute in the early trials can expect to reach an additional 1.7% jargon in the final trials (1.70 coefficient,.53 correlation, 4.21 t-test, $P < .001$).[14]

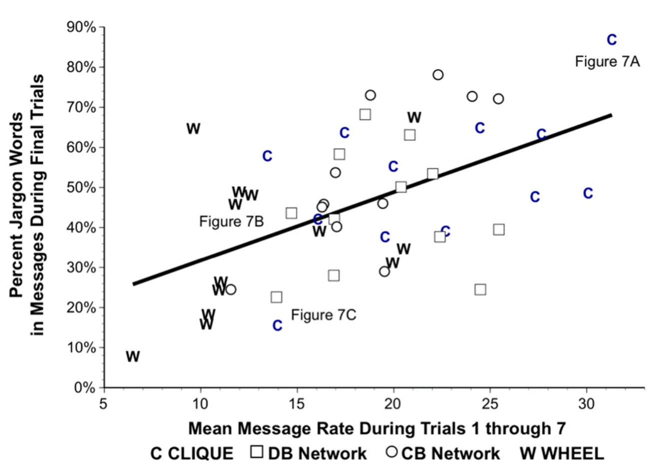


Fig. 11. Faster Pulse, Higher Percent Jargon, NOTE — Percent jargon during final trials (13, 14, 15) in 48 teams sorted on the horizontal axis by the average team message rate across the initial seven trials.

Beyond providing our clearest prediction of percent jargon, network pulse's motivation to engage in jargon dominates network structure's control over access to jargon information. Controlling for the four assigned networks in Fig. 6 offers negligible improvement to Fig. 11 (0.74 $F_{(3,43)}$, $P \sim .53$), as does controlling for message concentration from Fig. 9 (−0.95 t-test for log behavioral concentration added to the

[14] The improved prediction in Fig. 11 comes with a question about endogeneity. Almost half of the trial to trial variation in team message rate is within teams (versus 5.2% for message concentration, see Table S5 in the online supplement). The variation within teams could be enabled by variation in percent jargon: As teams converge on jargon, their messages can be shorter, which means they can send more of them, increasing the message rate. We address the reverse causality issue as best we can by computing the message-rate predictor during early trials to predict percent jargon computed during the final trials, distinguishing "early trials" by a discontinuity in the drift into jargon (trials before trial 8, see the final section in the online supplement). Endogeneity is not eliminated, of course. Using early pulse to predict final use of jargon merely gives us more confidence in the Fig. 11 association to dig into it further.

regression in Fig. 11, P ~.35).[15] More, percent jargon is not correlated with message volume or team time so much as it is correlated with the network pulse measure: messages per unit of time.[16]

5. Conclusions and discussion

We set out on a path to study jargon's virtues and pathologies as a topic in network theory and management research. We analyze data from a renovated classic network experiment from which we present empirical support for three hypotheses. (H1) Teams moving down their learning curve to greater efficiency are prone to shared jargon. This is less a surprise, given the history of work on learning curves, than it is a documentation of jargon as our dependent variable. As a team moves down its learning curve (Fig. 1), language drifts away from day-to-day speech (Fig. 2) and into jargon (Fig. 5).

The social network within a team affects the drift into jargon. With respect to network structure, shared jargon is less likely to emerge in teams wherein communication is concentrated in a single teammate. This prediction, adapted from the "centrality hypothesis" familiar in a history of research on networks and team performance (H2), is supported with respect to the networks to which teams are randomly assigned in the experiment (Fig. 6), but better supported with respect to the behavioral network structure that emerges during the experiment (Fig. 9). With respect to network pulse (Fig. 10), jargon is more likely to emerge among colleagues who communicate at a rapid rate (H3). Network structure and pulse overlap conceptually. They both involve access to information and learning. But they are distinct in their mechanism; structure operates by controlling access and pulse operates by creating motivation to access. Network structure predicts jargon in our data (Figs. 6, 9), but stronger prediction comes from network pulse — the rate at which colleagues communicate. The more numerous and crowded the communication efforts among colleagues, the more likely they converge on shared jargon (Fig. 11).

We see two contributions from the paper. Our primary contribution is to open a door on colleague jargon as a performance indicator for network theory and management research. Our results are based on a single experiment, but this is not an isolated study. Our experiment is a modest renovation of a classic experiment that spawned a great volume of replication work. We have simply used what we learned within that tradition to sketch a story about colleague jargon, performance, and their network origins.

Our second contribution is to distinguish network pulse from structure as a performance predictor. Quite apart from the stronger prediction provided here by network pulse, the predictors differ in their mechanism — structure by providing access, pulse by providing motivation to access. Digital sources of network data make it possible to study pulse in ways previously difficult or impossible. As pulse data are explored, it will be interesting to see how network pulse plays against structure on topics traditionally predicted by structure.

Obvious next steps are replication to alleviate limitations of the evidence presented, and exploration from the conceptual platform provided. Beyond the usual virtues of having similar studies replicate our reported association between network pulse and jargon, it would be reassuring to see (1) studies in which the social network a subject brings into the experiment is measured to confirm the source of differences between assigned and behavioral network structure, (2) field or experiment studies in which the endogeneity of pulse can be measured as a control variable, (3) field studies in which the emergence of jargon in project teams outside a behavioral lab is linked to network pulse.

There are a great many research directions for exploration from the conceptual platform of network structure and pulse as social origins of jargon. In closing, we highlight a few viewing jargon from inside, then outside, the team.

Inside the team, consider colleague visibility as the team expands. In our experiment, colleagues are most visible to subjects assigned to a CLIQUE network. Even in a CLIQUE, however, subjects only see the messages they send and receive. Subjects are blind to messages between colleagues. But surely the incentive to adopt jargon in one's own messages is enhanced when you see two colleagues find amusement and understanding by using the term with one another (Chwe's, 2001, image of "common knowledge," in which everyone knows what others know, and know that everyone knows). By blinding subjects to jargon exchange between teammates, the communication networks in the study experiment fall short of the real-life incentive for jargon, such that our results under-estimate network effect. The small size of the study teams might alleviate the lack of witnessing colleague exchanges, but in larger teams, much of what passes for jargon is words and phrases we overhear colleagues discussing, or our children using with their friends, or celebrities using in mass media accounts.

Network size raises another question. Maroulis et al. (2020) run the Bavelas-Leavitt-Smith experiment increasing network size to make the task complex. Instead of five teammates, Maroulis et al. assemble teams of 20 subjects organized into four subgroups. Consistent with the centrality hypothesis, the more dense the connections between teammates with different information, the faster the team as a whole solves the task — dense ties among subgroup members who have diverse information (the "diversity" condition), or dense ties between subgroups within which information is homogeneous (the "flat8" network in the "homogenous" condition). The fastest teams feature connected brokers between the subgroups ("cent2," "Flat2," "Cent8" conditions, akin to the CB network in Fig. 6), which raises a scale question: At what size network does the local leadership that inhibits convergence on jargon in 5-person teams (Fig. 9), facilitate convergence on jargon within teams of teams? And is the scale question a matter of people or subgroups?

There is also analytical traction in studying the roles people play inside the team. The network pulse experienced by individual subjects depends on their position in their assigned network. Subjects assigned to the leader position at hub of a WHEEL network have higher message rates than subjects assigned to a subordinate position (Fig. 10B for illustration). On average, subjects assigned to the hub-position in a WHEEL network have a pulse of 5.72 messages per minute of team play during the initial seven trials. Subjects assigned to one of the subordinate positions average a pulse of 1.89 messages per minute. The higher message rate for leaders gives them greater incentive to engage in

[15] We also tested for motivation created by early success in the experiment. Network pulse motivates by pushing teammates to keep up with one another. Early success in the experiment could create a more positive motivation of doing well at something so subjects are encouraged to do better. Percent jargon in the final trials is correlated with early success:.37 correlation with average number of teammate correct guesses during the first three trials (0 up to 5), and a smaller.11 correlation with correct guesses during the second three trials. Teams were given a bonus when everyone on the team guessed correctly. Percent jargon is correlated.36 with the number initial trials in which a team received the bonus (1, 2, or 3), and a smaller.17 correlation with number of bonuses in second three trials. However, none of these early success variables adds to the prediction in Fig. 11 (1.40 t-test for number of correct guesses in first three trials, and 1.33 t-test for number of bonuses, P < .17). Being shoved by network pulse dominates being encouraged by early success.

[16] Below matrix shows correlations between message variables and the percent of words in messages during the final three trials that are jargon (as in Fig. 11). Correlations in the upper diagonal are across individual subjects ($N = 48 \times 7 = 336$). Correlations in the lower diagonal are for team message variables averaged across teams (as in Fig. 11, N = 48).

Percent Jargon in Final 3 Trials	Message Variables in Initial 7 Trials		
	Messages	Minutes	Messages/Minute
1.00	.08	-0.09	.44
.15	1.00	.84	.08
-0.25	.56	1.00	-0.37
.53	.61	-0.26	1.00

jargon, but the higher message concentration in one teammate lowers the rates for colleagues, and so lowers teammate incentive to engage in jargon. To what extent is team convergence on jargon a function of having a teammate highly motivated to engage in jargon? If the key to shared jargon is getting a potential jargon word into discussion, then the most motivated teammate could be critical. If the key is getting teammates to agree on it, then multiple interested teammates matter, and the least motivated teammate could be a drag on convergence. Percent jargon in our final trials is more correlated with the minimum teammate message rate (0.41, versus.21 for the maximum message rate). In other words, shared jargon is less about someone getting the process started than it is about keeping everyone involved. In contrast to the usual story about network brokers leading groups into high performance, this is a story about network brokers being an obstruction to teammates feeling the network pulse that pushes people to find shared jargon. The anonymity of messages means that network rules of etiquette are less revelatory here than the rules can be in face-to-face discussion (e.g., Gibson, 2005). It would be interesting to have video data of teams coordinating face-to-face on the tangrams.

Viewed from outside the team, a consequential element missing in the study experiment is other groups. The messages we studied are extemporaneous and expressed with relative anonymity, so they probably contain temporary personal emotions more often than would electronic exchanges explicitly written as part of a historical record (e.g., Orlikowski and Yates, 1994:551 n). The latter are more likely to preserve language consistent with the broader organization in which teammates are embedded. More, groups typically exist within a status hierarchy in which jargon cascades down the hierarchy, and jargon can serve to reinforce boundaries around community members. Cascading jargon is nicely illustrated in Brown et al. (2020:277,279); demonstration that acronyms are more likely in the titles of dissertations and theses from lower-rank schools. Boundary-maintenance jargon is illustrated by academic communities held together by commitment to their jargon rather than the value of their work (fill in your favorite example here). In short, our analysis of jargon's network origins ignores status. We focus on jargon as an enabling correlate of specialization and social clustering. Looking across the hierarchy of groups in which any one team is embedded, however, there is a world of status-based jargon to be explored, much of it likely rich in jargon pathologies.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.socnet.2022.05.002.

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