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Fuzzy Cognitive Maps (FCMs) In Communication

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FUZZY COGNITIVE MAPS (FCMs) IN COMMUNICTION

BY

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Abstract

This research analyzes the communication patterns of teams, based on their team performance, in order to understand the relationship between team communication and team performance using fuzzy cognitive maps (FCMs). A two-pronged methodology was executed: (1) communication data processing by (a) classifying utterances into flow, (b) content, represented as speech acts, and (c) validation, and (2) analyzing the communication patterns using augmented FCMs. The strengths of the relationships among key communication concepts were estimated and compared between the ten teams' FCMs both quantitatively and qualitatively. For the comparison all the FCMs were separated into low performing teams (LPTs) and high performing teams (HPTs) according to their performance score (project grade in this case). Quantitative analysis included the calculation of intraclass correlations (ICC), as well as the testing of equality in means and variances between the two groups. Qualitative analysis looked at the different maps to find patterns in the connections. The results from the ICC show that LPTs were definitely homogeneous, but while HPTs did not pass the threshold to be considered homogeneous, they were close enough and as such cannot truly be classified as heterogeneous. Results of the test in means and variances show that although none of the means could be considered significantly different, some of the variances were. This would indicate that while LPTs might have a particular communication pattern that leads to low performance, HPTs have several communication patterns that lead to high performance. Further analysis is needed in order to better understand FCMs in communication and the use of the different FCM metrics available to interpret them. Furthermore, a deeper look is needed into FCM comparison metrics to determine which metric(s) is/are best suited for the analysis team communication FCMs.

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Preface

This paper is written in manuscript format for publication in the *Human Factors* journal. At the time of submission to the graduate school, this paper has not yet been submitted to the journal for review.

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MANUSCRIPT INTRODUCTION

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INTRODUCTION

The 21st century is an era of big data, project teams, and ubiquitous communication; but scientifically speaking, what goes into effective team communication is still unclear and even more relevant in today's workplace. Texting, virtual meetings, and gaming technologies have assisted in growing understanding of how people decide to communicate. Even through these environments, however, communication is limited and bounded by those domains, thus making it difficult to transition knowledge back to human-to-human communication. This research aims to better understand how communication patterns between team members relate to overall team performance by exploring strategies and layers associated with the Fuzzy Cognitive Maps (FCMs).

Different methods of analyzing team communication already currently exist. However, none of them claim to be able to analyze both *flow* and *content* of the communication simultaneously. FCMs, a synthesized mixture of fuzzy logic with cognitive mapping based in graph theory, were tested in an attempt to fill this gap in knowledge. Understanding team dynamics and communication would allow the selection and formation of more productive and high-performing teams. In order to initiate this exploration, the Architectural, Engineering, and Construction (AEC) industry was selected based on its inherent, symbiotic relationship of successful projects via successful teams. Identifying FCM as an appropriate technique that can analyze "who is talking to whom" (*flow*) and "what they are saying" (*content*) simultaneously is paramount to the future success of larger project teams.

This research analyzes ten teams based on their team performance (i.e., four successful and six unsuccessful teams) using communication patterns limited to specific content. Content here was predetermined since not all the conversation was analyzed. Flow consisted of the circulation of people talking and the content of that communication. Previous studies utilized FCMs as a method of analyzing dyadic communication in an anti-air warfare coordinator (AAWC) simulator (Kim, Macht, Rothrock, & Nembhard, 2014), but not with larger team sizes or within the AEC domain. Comparing extremes of team performance provides ample opportunity to demonstrate whether communication patterns are similar or different when controlling for specific content, tasks (Kwasitsu, 2003; Lonergan, Long, Bolin, Neuman, 2000; Allen, 1966; Driskell, Hogan, & Salas, 1987) and environments (Poole, 1999). Preliminary research conducted by Engome Tchupo, Sreeramakavacham, Kim, & Macht (2017) provided initial evidence that FCMs can analyze and differentiate communication patterns between teams of extreme performances in terms of both content and flow. They found that the high performing teams (HPTs) tended to communication more proactively, as evidenced by the ratio of indegree of "Response to Information Request" to outdegree of "Requesting Information". The ratio showed that about 25% more information was requested and answered by the HPT than by the low performing teams (LPTs). The work presented here, therefore, aims at expanding and further exploring the given method using a greater number teams with extreme levels of performance to truly vet the methodological process of comparison. This methodology could provide as an effective tool in aiding the understanding of how communication patterns impact team performance. The research questions investigated in this work are:

1. Can FCMs capture the similarities between teams in with the same level of performance?
2. Can FCMs differentiate between teams at opposing ends of the performance spectrum?

The overall aim of the research is to test whether content and flow of communication can be seen and studied simultaneously using FCMs. If these research questions turn out to be positively verified, it will provide empirical evidence to further support previous work done in team communication (Bowers, Jentsch, Salas, & Braun, 1998; Cooke, Duchon, Gorman, Keyton, & Miller, 2012; Gorman, Cooke, Amazeen, & Fouse, 2012) while adding the combined flow and content model via FCMs. Additionally, it will formalize the methodology initially studied and put forth by Engome Tchupo, et al. (2017), Kim, Macht, and Lee (2012), Kim et al. (2014), and Stylios, Georgopoulos, Malandraki, & Chouliara (2008) in understanding how FCMs can be used to study communication patterns.

PRIOR LITERATURE

Communication is the primary vehicle for interaction between individuals. Communication data can provide a rich record that assists with understanding cognition (Cooke et al., 2012; Stevens, Galloway, Wang, & Berka, 2012). Cognition is important because it is how one processes the problem and how they go about solving it that might help researchers understand the *what* and *how* of their performance. However, as it is not possible to understand a person's or a group's thought process without it being verbally articulated, the only way to try and capture it is through communication. In the case of groups, the focus is not so much on the individual members' cognition, but rather on the group cognition, also known as shared cognition. Shared cognition is different from individual cognition in that the knowledge built during this time is only possible with human interaction (Clark & Brennan, 1991).

Based on information theory (Shannon & Weaver, 1949), communication is defined as a sequential process to deliver a sender's encoded ideas or message to a receiver through a communication channel. Traditionally, communication is separated into two components: content and flow (Cooke et al., 2012; Stevens et al., 2012). Content is considered to be the verbal or nonverbal attributes of a discussion between more than one individual (Cooke et al., 2012; Gorman et al., 2012; Khawaja, Chen, and Marcus, 2012). Flow refers to how the content is transferred between subjects, human or otherwise, to determine who sent the message (Bowers et al., 1998; Cooke et al., 2012; Khawaja et al., 2012), but not who specifically received the message (Stevens et al., 2012). Speech is sequential, temporal, and relational, as people tend to speak one after another, and what is currently being said is generally preceded by another's speech or action (Gorman, 2013; Marks, Mathieu, & Zaccaro, 2001).

Researchers have long studied the *effects of communication* on different aspects of life and work. In the literature, many studies have shown the linear or polynomial relationships between communication frequency and performance (Allen, 1977; Patrashkova-Volzdoska, McComb, Green, & Compton, 2003). However, studying the relationship between the effectiveness of communication content and flow, simultaneously, and their team performance has proven to be particularly complicated. In 2012, Cooke presented existing methods for the analysis of communication, as well as where the gaps still exist (Table 1). This research attempts to fill one of these gaps: Static communication with respect to Content + Flow (Highlighted in Table 1). Fuzzy Cognitive Mapping (FCM) could represent the mental model of a team's communication flow and content. It could also be used to show not only the flow of conversation between people, but also the flow within the content of the conversation. Currently, the x coordination score method (see Table 1) is the only methodological approach to communication that captures both content and flow, simultaneously. The main difference between the x coordination score method and what this research is exploring is the timing. X coordination score looks at content and flow at time intervals, while this research is attempting to look at content and flow as an aggregate over time; thus, for the entire conversation at once.

Table 1: Communication Methodological Approaches (Adapted from Cooke et al., 2012)

		Content	Flow	Content + Flow
Aggregate over time	**Static**	*Word counts*		
Order of speakers	**Sequential**	*LSA lag coherence*	*ChainMaster*	
Time Intervals	**Timing**		*Cumulative recorder*	*X coordination score*
		- Transcription of communication - Meaning	- Who's talking to whom - When/how long	- For selected events: - Who's talking to whom - When/how long - Asking/passing

FCMs combine fuzzy logic, proposed by Zadeh (1965) and later elaborated by Kosko (1986), with cognitive mapping. FCMs are a method for modeling dynamic systems, and have been applied in many different fields to transform linguistic data into quantitative data (Kim et al., 2012; Kim et al., 2014; Eden, 2003). FCMs list fuzzy sets (uncertain sets) related to events to show the flow paths and help in representing and computing the strength of impacts in a causal flow path (Kosko, 1986). As cognitive maps (CMs), directed network graphs with causal connections, cannot handle partial truths (i.e., things that are true only to an extent), they would not normally be able to represent team communication flow. Mental models, such as team communication flow, need a method that can represent ambiguities between variables or connections, in which case, FCMs are more useful than general CMs (Kosko, 1986). A proven method to account for the uncertainty of human mental model is using fuzzy sets (Berkes & Berkes, 2009; Kim, Rothrock, and Tharanathan, 2016). Since human communication flow is inherently fuzzy in nature (Wang & Chang, 1980), FCMs can represent structured knowledge, complex system models, and linguistic data (León, Rodriguez, García, Bello, & Vanhoof, 2010).

There exist multiple types of FCMs with the three most commonly used ones are binary, trivalent, and sigmoid (Tsadiras, 2008). A binary FCM can only indicate whether or not one node/concept affects the other. A trivalent FCM allows for a deeper expression of the different causal relationships in the network. With a trivalent FCM, it is possible to express whether a node/concept decreases the other, does not affect it, or increases it. Finally, there is the sigmoid FCM which can not only show which node decreases or increases the other, but also by how much it decreases or increases it (Tsadiras, 2008). Here, trivalent FCMs are used because they provide more information than binary FCMs and do not have the complexity in calculation and the relative, complex meaning of sigmoid FCMs. By analyzing communication flow patterns between team members using FCMs, researchers can discern the difference between teams of varying degrees of performance (Stylios et al., 2008). FCMs are also not limited to linear relations among variables, and focus on qualitative information, as such, they can represent and analyze the effectiveness of team communication.

METHODOLOGY

For the analysis of the data in this research, a mixed methods approach was undertaken. Mixed methods refer to the execution of both a quantitative analysis and a qualitative analysis (Creswell, 2014). There exist several different categories of mixed method; of which one was selected for this research. This method is known as exploratory sequential mixed methods. Exploratory sequential, is when a qualitative analysis is done first and later followed by a quantitative analysis. In this mixed method, qualitative and quantitative analyses are carried out and results are obtained from both of them separately. The assumption is that the results from the quantitative analysis will help support the results obtained from the qualitative analysis. However, for this study, the use of the exploratory mixed method was only partial. Where the quantitative analysis was applied, there were no qualitative methods that could showcase the same information provided, and vice versa.

Teams & Task

The teams were tested in an academic environment making observable statistical effects more difficult to obtain than in a lab setting, yet providing a view of the teams more akin to a field setting. All teams were composed of undergraduate engineering students in a construction management course at the end of their third year of a five-year program. By the time the project was assigned and experiment underway, most of the students had acquired basic knowledge of AEC principles and familiarity with their peers. With respect to the experiment, the teams were essentially formed at random (e.g., individual preference) and participation was voluntary without financial compensation.

For this research, each team was invited into a collaborative workspace to draft commercial site utilization plans (i.e., layout of materials and machinery with respect to a construction site) and a site schedule (i.e., corresponding time frames of all various movements) for the phases of construction. Already familiar with the commercial project, as it had been used as a semester long project in the course, no portion of this aspects of the project was disseminated prior to the team's arrival. A basic site utilization plan was presented on a SMARTBoard™ (i.e., an electronic whiteboard) to seated students at a table placed directly in front of the technology. Each team was allowed up to 45 minutes, uninterrupted, to brainstorm and develop their site plan; early exits were not penalized. The resulting site utilization plans were not graded, but used as the foundation for the final submissions where their grades were established as the team performance. Communication data was collected during this phase for the site utilization plan and was the only time the groups were observed. The final site plan and schedule were submitted about three weeks after the observed session occurred. The research assumes that whatever communication patterns existing within the teams during this session were constant over the course of those following weeks. Out of a total pool of 45 teams collected between 2013 and 2015, ten were selected based on their extreme team performances; i.e., the highest and lowest performances (grades) exceeding ±1 standard deviation from the normalized means across all years. The same methodology from Engome Tchupo et al. (2017) but a substantial extension in terms of number of teams. These teams were comprised of three to four members with 38 participants overall; a total of 9 females (23.68%) and 29 males (76.32%).

Communication

Each participating team was video recorded in the collaborative workspace, isolated from external influences. Cameras were placed throughout the workspace, as well supplemental audio when necessary. Prior to video analysis, third party professionals transcribed the conversations, resulting in details such as utterances and word count. Each video was analyzed in three steps: (1) flow, (2) content, and (3) validation.

The first step in the analysis, flow, refers to identifying who was talking to whom. The second step, content, looked at topic, and speech acts. The first part of content was assessed using standardized, ubiquitous communication topics on all site plans for the AEC industry and required each project year by the professor. These five topics were: trailers, roads, fences, sanitation, and parking while requirements for setting up a work schedule and organization were coded under an additional label, 'coordination'. Anything outside of these resulting six topics was considered noise and thus disregarded in this analysis.

When data coding, more than one of the six topics could be selected for any given utterance depending on the information contained in the line of dialogue. As the six topics considered do not cover the entirety of the conversation, it was necessary to understand exactly how much of the conversation was actually considered. For this, the total number of utterances in each conversation were counted, as well as the total number of utterances. Utterances were looked in lieu of duration due to the complexities of linguistics that play a role on the time (in minutes) that conversation covered. The values obtained were grouped in terms of HPTs and LPTs with the means and variances tested for statistical significance. The initial analysis determined how much data was analyzed, in total, in this research. Results found that for both HPTs and LPTs, on average, the same amount of the conversation was analyzed (32.41% and 32.42% respectively). The amount of conversation analyzed for HPTs ranged from 19.66% to 46.26%, while that of LPT ranged from 25.74% to 45.98%. When testing for statistical differences between the HPTs and the LPTs, the means ($p = 0.872$) and the variances ($p = 0.347$) had no statistical significance.

Speech acts (SAs), the next part of analysis of content, classified each utterance according to the general concept or explanation behind it (Stevens et al., 2012; Macht, 2014) and an utterance could include one or more speech acts. To illustrate the use of these speech acts, Table 2 is an excerpt of a coded conversation. These SAs include "Requesting Information" (RI; e.g., Line 1 in Table 2), which is used when someone asks an open-ended question. "Requesting Confirmation" (RC; e.g., Line 3 or Line 4 in Table 2) is used when someone asks a yes/no or an either/or question. Both of these requests can be answered either with "Response with Information" (RwI; e.g., Line 2 in Table 2) or "Response without Information" (RwoI).

“Response with Information” is used when someone replies to a “Requesting Information” or “Requesting Confirmation” with something that helps move the project forward. “Response without Information” is used when the answer given does not provide any useful information for the continuation of the project. An example of such a case, although not provided in the table, is if someone were to answer a question by simply saying “I don’t know”. “No Response” (NR) is to describe when a person asks a question and the person speaking immediately afterward does not answer that question. After a “No Response” (NR), however, the question could still be answered by someone else or in the next utterance (e.g., Line 4 in Table 2). “Providing Information” (PI) is used when someone either answers a question and then adds detail (e.g., Line 5 in Table 2) or gives information unprompted by a question. The final action, “Statement” (S), refers to any short sentences or exclamations that are pertinent to the topic, but does not productively contribute to the project. Step 3) validation, involved another researcher reviewing any questionable utterances and classifying them accordingly.

Table 2: Example Excerpt of Team Conversation

Line	Person	Transcript	Topic	To				Speech Act
				P1	P2	P3	P4	
1	P1	So what do you think…?	Roads				X	Requesting Information
2	P4	This looks like it's easier to get down, so I think the temporary road should come from that side…	Roads	X				Response with Information
3	P1	11th Street	Roads		X	X	X	Requesting Confirmation
4	P2	What about 12?	Roads	X			X	No Response Requesting Confirmation
5	P4	… And not 12th because 12th looks…	Roads	X	X			Response with Information Providing Information
6	P1	Okay, but where do you see that you can get into the site from 11th Street?	Roads				X	Response with Information Requesting Information

Assumptions were made to define potential nebulous areas of inconsistency. First, if the person speaking was looking at a particular person, it was assumed they were addressing that person; if they were looking at the SMARTBoard™ or at the papers (assignment sheet, class notes, etc.), they were assumed to be addressing the whole group. Here, certain aspects of nonverbal communication were included despite the study focusing solely on verbal communication. Next, if the person replied to a previously asked question, they were assumed to be talking to the person who had asked the original question. When unsure of what topic was being discussed, it was assumed that the group was still discussing the last identifiable topic. Finally, on certain occasions, when a person started an utterance by addressing one particular person and then switched either to someone else or to the whole group (by moving gaze to another person for example), the utterance was split into different columns to mark who was being addressed in each part, even though the whole line of communication was counted as one utterance.

Team Performance

Team performances were project grades provided by the course's professor, an expert in the field. The project score was based on a percent score for the submission of both the site utilization plan and the schedule with multiple solutions viable for a successful execution of the task. Project scores were normalized for comparison purposes, teams that scored above one standard deviation were considered high performing teams and those who scored below one standard deviation were considered low performing teams. In team work, especially for project-based tasks, communication is the means by which ideas are shared and the entire team can be certain they are working towards their goal. As such, it can be expected that a lack of communication or improper communication could eventually lead to a failure in the task.

Fuzzy Cognitive Maps

The various independent activities in a network system could be explained by using causal flow between nodes (Kosko, 1986). As previously mentioned, there are multiple types of FCMs: binary, trivalent, and sigmoid (Tsadiras, 2008). In a binary FCM the arcs can only accept values of 0 or 1 indicating that one node/concept either does not activate the other, or that it does respectively. A trivalent FCM has arcs which can assume values of {-1, 0, 1}; representing that the one node/concept decreases the other, does not affect it, or increases it, respectively. Lastly, a sigmoid FCM has arcs able to receive any value between -1 and 1 allowing to show both what nodes/concepts do or do not influence others as well as their level of influence. This research uses trivalent FCMs in an effort to provide enough information to truly test out the methodology (compared to binary FCMs), without introducing unnecessary complexity (see sigmoid FCMs). It is quite possible that knowing the degrees to which different concepts affect others will prove more beneficial to the study of communication patterns, however it is necessary to first understand whether the application of FCMs in this manner works for simpler cases prior to attempting a more complicated analysis.

Trivalent FCMs are formed for each one-on-one conversation within a group. That is, for groups of four team members there are six individual FCMs and for groups of three team members there are three individual FCMs. An augmented FCM is developed by combining each group's individual one-on-one FCMs using Equation (1) (Kosko, 1996) which represents the fuzziness in a networked system.

$$F = \frac{1}{n}\sum_{i=1}^{n} W_i F_i \tag{1}$$

where F_i = i^{th} FCM in the system; W_i = the weight of the i^{th} FCM.

Figure 1 illustrates the process for a team with three members. The augmented FCM induces the interaction of causal concepts for all important actions. The estimate of F depends on the sample size, in our case team size, selected; the larger sample size the better. By using the key concepts (SAs) defined from the communication data, trivalent FCMs were developed with each of these seven SAs represented as the nodes. Each team's communication patterns were developed through this process, each resulting in a team, augmented FCM. Once completed, comparisons between each team resulted in augmented FCMs being separated into extreme performances of LPT and HPT, to be examined quantitatively and qualitatively.

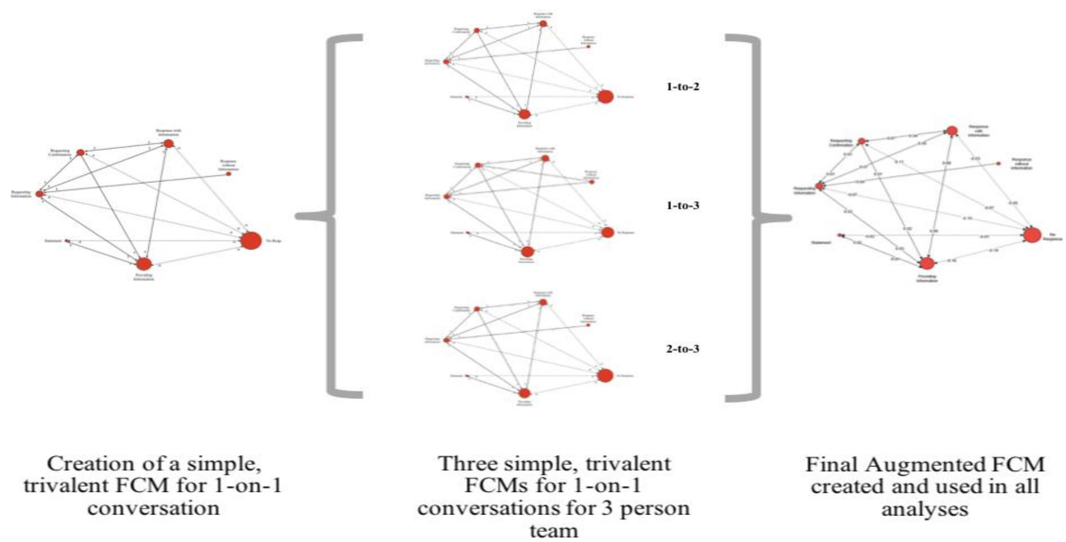

Figure 1: Transition Process from Simple, Trivalent FCMs for a 3-Person Team to Augmented FCMs

There are two aspects of an augmented, trivalent FCM to note: the value of the edge and the size of the node. Firstly, the FCMs created were trivalent with edge values being {-1, 0, 1} (Tsadiras, 2008). A '-1' indicates the exchange of information between those nodes, which in turn means that it did not help the team to achieve their task. A '0' value indicates that there was no communication with respect to the actions and does not appear in the map, as no arrow/edge is required. A '1' represents that the exchange of information between those nodes was relevant and helped the team achieve their task. These discrete node values are seen in the individual FCMs to capture the one-on-one conversations. For the purpose of this study, team FCMs (also known as augmented FCMs) were analyzed. Equation (1), therefore, was applied to these different trivalent FCMs to create an overall augmented FCM that is a representative aggregate of these one-to-one FCMs for the entire team. This resulted in FCMs that resemble sigmoid FCMs in that the edges have continuous values between -1 and 1. They are, however, still considered trivalent, augmented FCMs because the base FCMs that formed these aggregated maps are trivalent and elements required for the creation of sigmoid FCMs (e.g., threshold values) are not included. Secondly, the size of each node in an augmented FCM could be interpreted as the amount of the information being transmitted or received from other nodes. Three metrics that look at the edge values and node size for interpretation of FCMs are: indegree, outdegree, and centrality (Yoon & Jetter, 2016). The *indegree* shows how each node is influenced by other nodes and is the summation of the absolute value of the weight on the input links. On the other hand, the *outdegree* indicates how each node influences other nodes, and is the summation of the absolute value of the weight on output links. The *centrality* is a measure of how strong direct connections of a node is with other nodes in the augmented FCM and is the summation of the absolute value of the weights of both input and output links (Reimann, 1998).

Statistical Analysis Techniques

After the FCMs were obtained, inter rater reliability (IRR) was calculated in the form of intraclass correlation (ICC). This test would allow us to see if the teams grouped together (HPTs and LPTs) could truly be considered as homogeneous or heterogeneous groups. This research was carried out under the assumption that all HPTs had similar communication patterns and all LPTs had similar communication patterns. ICC is an estimate of IRR at the level of the individual rater; in this case, teams (Shrout & Fleiss, 1979; James, 1982). ICC(1) represents the variance in team member responses (Rehim, DeMoor, Olmsted, Dent, & Parker-Raley, 2017; Kirkman, Tesluk, & Rosen, 2004; Steward, 2006; Bliese, 2000) and an ICC(1) ≥ 0.7 represents homogeneity in raters as defined in Bliese (2000). Meanwhile ICC(2) represents the reliability or stability of group/team means (Kirkman et al., 2004; Bliese, 2000) and an ICC(2) ≥ 0.7 indicates stability in these means (Kirkman et al., 2004). In this case, the hypothesis is:

Hypothesis 1a: LPTs are homogeneous with respect to differences within the group.

Hypothesis 1b: HPTs are homogeneous with respect to differences within the group.

This, in turn, would enable us to answer the first research question on whether FCMs can capture the similarities within teams of the same group.

Next, the LPT and HPT groups were tested for equal means and variances using the Brown and Forsythe modification of Levene's test (Levene, 1960; Brown & Forsythe, 1974). This method uses the sample median rather than the sample mean, making it more robust than Levene's test (Brown & Forsythe, 1974). This test was used to compare the LPTs and HPTs in terms of the amount of conversation analyzed, as well as the indegree, outdegree, and centrality for each SA. Where necessary, the threshold was set to $\alpha=0.05$ for all analyses to provide for more reliable results with less chance of error. From the results of the various analyses, a higher alpha (e.g., $\alpha = 0.1$) would only change the significance of one factor. This analysis was done as a way of testing whether HPTs and LPTs as a group were statistically different on a basic level (means and variance). Thus, the hypotheses when carrying out this analysis are:

Hypothesis 2a: LPTs and HPTs will differ with respect to mean between groups

Hypothesis 2b: LPTs and HPTs will not differ with respect to the variance between groups

This will help answer the second research question on if FCMs can differentiate between teams on opposite ends of the spectrum.

Similar to Engome Tchupo et al. (2017), the ratio of indegree of RwI to outdegree of RI was calculated for HPTs and LPTs and compared. Again, the ratios were divided into their respective groups (LPT and HPT) with the mean and variance of these values tested for statistical significance. The results help understand whether the difference in the amount of information carried and received was prevalent through all teams on opposite ends of the spectrum or merely present in certain teams. As the speech acts used in this research are slightly different from those in Engome Tchupo et al. (2017), two additional ratios were required to better capture this same information. The ratio of indegree of RwI to outdegree of requests (i.e., RI and RC both) was calculated and analyzed. This was executed due to the fact that unlike Engome Tchupo et al.

(2017), RI is not the only request node that can lead to a RwI. Additionally, the ratio of indegree of NR to outdegree of requests was calculated and analyzed. This ratio gives similar information to the previous one, only instead of looking at the amount of information that was provided in relation to the amount requested, it looks at the amount of information that was not provided despite it having been requested.

Qualitative Analysis

In addition to the statistical analysis run on the different FCMs, a qualitative analysis was executed in order to execute an exploratory sequential mixed method analysis. As previously mentioned, the application of this mixed methods was only partial. Mainly because quantitative analysis was not possible without new, further exploratory research into various additional FCM metrics and methods. At the moment, the exploratory sequential analysis simply involved describing the behaviors seen in the maps and which SAs influenced other SAs by looking at where the arrows were coming from, as well as the size of the nodes.

RESULTS

The resulting team, augmented FCMs are displayed below; Figure 2 illustrates all four FCMs for the HPT group while Figure 3 shows the six FCMs for the LPT group. It is from the values obtained from all these graphs that the qualitative and quantitative analyses were performed.

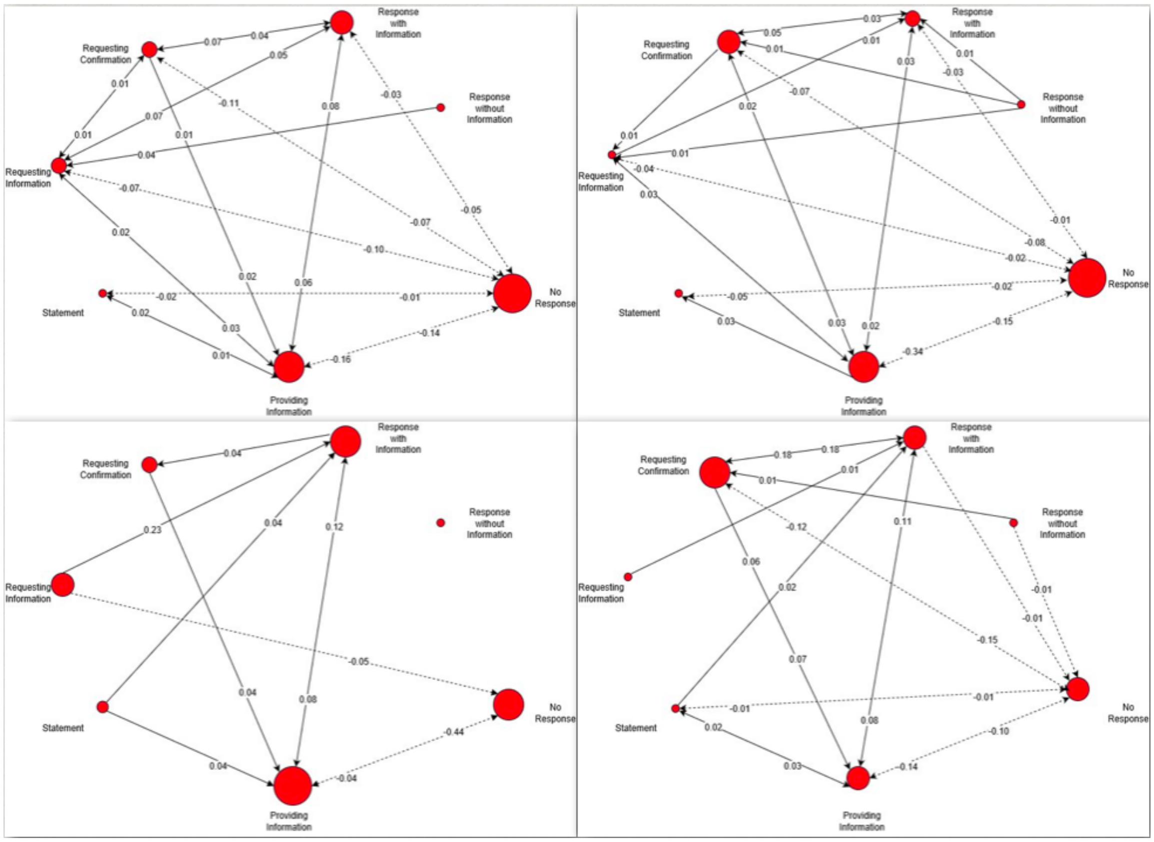

Figure 2: FCMs of the HPTs Group

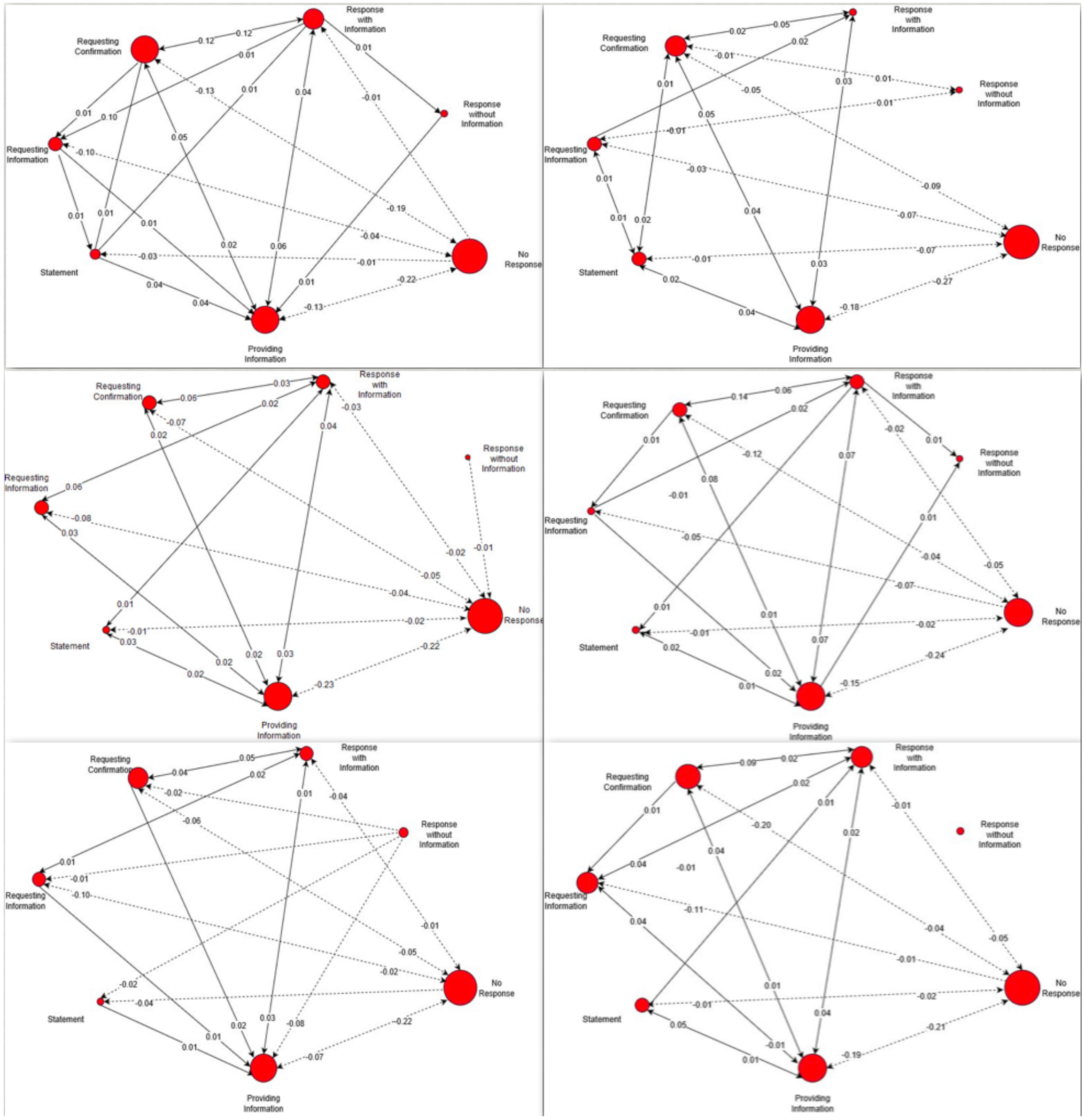

Figure 3: FCMs of the LPTs Group

In testing the ICC, LPTs and HPTs were tested separately, thus LPTs had six raters (or members of the group; a rater is traditionally classified in intraclass correlation as being one of the teams within that group) and HPTs had four. The subjects were indegree, outdegree, and centrality of all the speech acts, totaling 21 subjects (rows of evaluation) for both groups. For LPTs, the ICC(1) = 0.862 and ICC(2) = 0.86 with a $p < 0.001$ are statistically significant, thus the homogeneity in the raters while representing a stable group dynamic for all six teams; supporting *Hypothesis 1a*. For HPTs, the ICC(1) = 0.675 and ICC(2) = 0.670 with $p < 0.001$ are statistically significant, but are less than the 0.7 threshold, representing a heterogeneous rating and team dynamic; failing to support *Hypothesis 2a*.

Brown and Forsythe's modification of Levene's test was used to check for equal variances and means between the ratio of the indegree of RwI to the outdegree of RI for both the LPTs and HPTs. The results showed that the HPTs have a significantly greater variance ($p = 0.00$) than the LPTs which had no statistical difference between the means of the ratio. However, in the HPT group contained a team with a much greater ratio than any other team in the group. When this team was removed and the data tested again, neither the mean ($p = 0.849$) nor the variance ($p = 0.865$) were significant. After this test, outdegree of RC was added to the outdegree of RI. This changed the analysis to the ratio of indegree of RwI to the outdegree of requests (RI and RC). The results found neither mean ($p = 0.797$) nor variance ($p = 0.770$) as significant. In this case there were no outliers and therefore no additional data was removed. In both cases (indegree of RwI/outdegree of RI, and indegree of RwI/outdegree of RI and RC), the lack of statistical significance for both variance and mean indicates that both the LPTs and HPTs exchanged about the same amount of information.

The next ratio that was calculated and tested was the ratio of indegree of NR to outdegree of requests. When this was tested, like the other ratios, with the outcomes that neither the mean ($p = 0.063$) nor the variance ($p = 0.701$) were found to be statistically significant. This reflects that both the HPTs and LPTs exchanged about the same amount of no-responses to the total number of requests.

The same comparison was executed for each SAs between the LPT and HPT groups. Tables 3 shows the calculated means for HPTs and LPTs while Table 4 reveals the calculated variances for HPTs and LPTs. For example, in Table 3, the mean of outdegree for RC for HPTs is equal to 0.1838 whereas in Table 4, the variance of centrality of RwI for LPTs is equal to 0.0159.

Table 3: Comparison of Means for HPTs and LPTs

	High Performing Teams			**Low Performing Teams**		
Speech Acts	Indegree	Outdegree	Centrality	Indegree	Outdegree	Centrality
Requesting Information (RI)	0.0635	0.1239	0.1874	0.1376	0.0637	0.2013
Requesting Confirmation (RC)	0.1999	0.1838	0.3837	0.2326	0.1606	0.3932
Response w. Information (RwI)	0.2555	0.1819	0.4374	0.1299	0.1751	0.3050
Response w.o. Information (RwoI)	0.000	0.1118	0.0112	0.006	0.0281	0.0341
No Response (NR)	0.3540	0.3085	0.6629	0.3776	0.3740	0.7516
Providing Information (PI)	0.2978	0.3549	0.6527	0.2678	0.3455	0.6134
Statement (S)	0.0385	0.0452	0.0871	0.0524	0.0569	0.0024

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Comparison of Variances for HPTs and LPTs

	High Performing Teams			**Low Performing Teams**		
Speech Acts	Indegree	Outdegree	Centrality	Indegree	Outdegree	Centrality
Requesting Information (RI)	0.0069	**0.0165****	**0.0251***	0.0046	**0.0010****	**0.0038***
Requesting Confirmation (RC)	0.0206	0.0243	0.0870	0.0100	0.0106	0.0224
Response w. Information (RwI)	**0.0156***	0.0098	0.0316	**0.0017***	0.0084	0.0159
Response w.o. Information (RwoI)	**0.0000*****	0.0001	0.0001	**0.00004*****	0.0029	0.0026
No Response (NR)	0.0097	0.0427	0.0207	0.0084	0.0082	0.0082
Providing Information (PI)	0.0074	0.0190	0.0051	0.0010	0.0040	0.0080
Statement (S)	0.0010	0.0008	0.0002	0.0002	0.0021	0.0024

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The bolded cells within Tables 3 and 4 mark those means or variances that were considered statistically different between HPTs and LPTs noted with their level of significance. The results indicate that none of the means between HPTs and LPTs were considered significant, failing to support *Hypothesis 2a*.

There were four statistically significant areas for comparisons of variance between the two different types of extreme teams: indegree of RwI ($p = 0.0215$), outdegree of RI ($p = 0.00443$), centrality of RI ($p = 0.0148$), and indegree of RwoI ($p = 0.0000$), failing to support *Hypothesis 2b*. For the first three variances that were found to have statistically different (RwI; indegree and RI; outdegree and centrality), the HPTs had a higher variance than the LPTs; indicating, that the HPT group with fewer teams within the group were spread more than the LPT group. For the last statistically significant variance (RwoI; indegree), LPTs were found to have a higher spread instead. These results align with those from testing the ratio of RwI indegree to outdegree of RI as in both these cases, the means are shown to not being statistically significant while the variances are statistically significant.

Based on the results from the quantitative analysis, the qualitative analysis will focus on addressing the differences of RwI and RI first as part of the exploratory sequential mixed methods approach. When looking at the ratio of the indegree of RwI to the outdegree of RI, all the HPTs had a ratio greater than one. The same could not be said for all the LPTs, showing that more information was likely lost or not provided for the LPTs than for the HPTs. This did not hold true when the outdegree RC was added to that of RI. Now while much fewer teams have a ratio greater than one, the mean ratio for HPTs is still greater than that of LPTs at 0.762 compared to 0.710; not statistically significant.

Three additional observations were found beyond those initiated by the results of the quantitative analysis. First, in the HPT maps, RwoI had positive values on edges leading to RI, RC, and RwI (outdegree); meaning that RwoI positively influenced RI, RC, and RwI. Second, RwoI had 0 indegree; meaning there were no arrows from other SAs leading into RwoI. Third, the largest node (the node with the highest centrality) in all LPTs was the “No Response” node. This indicates that NR made the greatest overall contribution to the entire map and thus, conversation. Lastly, NR had negative indegree and outdegree values, thus, NR was negatively influenced by other nodes and influenced all the other nodes it interacted with negatively, respectively.

DISCUSSION

In analyzing of the amount of communication data considered during this research, it was shown that, as desired, there were no significant differences between the amount of information captured by this method for LPTs and HPTs. The results indicated that, as expected, neither of the groups had more of their conversation studied than any other group. Although some teams left earlier than others presumably due to completion of the assignment or at least the initial brainstorming, the topics considered in planning occupied about the same amount of conversation. This was important to know as one group having more data analyzed than the other could have significantly influenced further findings.

When testing for the ICC, the results partially supported the prior assumption that all teams within a group would have similar patterns; i.e., both LPTs and HPTs are homogeneous. The ICC(1) value of 0.862 for LPTs does indeed support homogeneity by exceeding the general threshold for homogeneity. Along with its ICC(2) value of 0.862, these results are stable, and accurately represent the different team means in this group. This indicates that while there are only six teams in the LPTs group, the overall group is balanced and does not necessarily require more data. Hence, this result should apply to entirely new LPTs within the AEC domain. These results support *hypothesis 1a* that LPTs are homogeneous with respect to the differences within their group. Homogeneity within the group indicates that the LPTs present a particular pattern of communication leading to their low performance. HPTs, on the other hand, are neither considered homogenous (ICC[1] = 0.675) nor stable (ICC[2] = 0.67). These results do not support *hypothesis 1b* claiming that HPTs are homogeneous with respect to the differences within their group. However, HPTs, although not homogeneous, are close enough that more data would be necessary to clarify the true patterns of the HPTs. Even with the p-value for ICC(1) being very small and statistically significant, the fact that the ICC(2) is below the threshold of stability ($0.67 < 0.7$) indicates that adding more teams could affect the results one way or the other. These results could indicate that unlike LPTs, the HPTs patterns are more varied, not only making it harder to pinpoint what exactly accounts for the differences between the two groups, but also pointing to the fact there might not be one particular communication pattern that leads to a higher performance.

From the comparative statistical analysis of the FCM metrics, there appears to be no significant difference between the means of the LPTs and those of the HPTs. This fails to provide evidence to support *hypothesis 2a* claiming that LPTs and HPTs will differ with respect to mean between groups; thus, the means between these two groups are statistically similar. The lack of statistical significance in the difference in means, demonstrates that on average, that teams provide and receive the same amount of information from the nodes (SAs). Therefore, any difference in pattern would not be found in the average amount of information sent from or received by the different nodes, but rather in their relationships to other nodes.

Significant differences when comparing variances, however, did exist four times: indegree of “Response with Information”, outdegree of “Requesting Information”, centrality of “Requesting Information”, and indegree of “Response without Information”. *Hypothesis 2b* is not supported because contrary to the prediction, LPTs and HPTs do differ with respect to variance between groups. HPTs have a higher variance in indegree of RwI demonstrating that the values for this specific metric are more spread out than the LPT group. This result indicates that HPTs tended to have more amounts of information being responded to within the conversation (indegree RwI node) over LPTs; meaning if ideas or thoughts were put out there in the conversation, high performance teams responded with helpful information. Similarly, a higher variance in RI outdegree signifies that the values for this metric varied significantly between HPTs and LPTs. HPT teams, therefore, not only respond with information (RwI) but they do indeed put more instances of communication out there asking their team members for information (RI) than LPTs. The higher variance in centrality of RI can be similarly explained and indicates that overall, the impact of these information requests on the conversation varied more among teams in the HPT group than those in the LPT group. RI's centrality, therefore, states that the shear variety of volume for instances of communication where team members request information from their team, a potential sign of trust, teamwork and/or collaboration, is stronger in HPTs than LPTs. This result makes sense because it aligns with the previous two results that HPT teams put more requests for information out to their team members while also receiving responses with that information back; demonstrating a potential sign of trust, teamwork and/or collaboration necessary for achieving team cognition. LPTs do not appear to practice this type of information or knowledge exchange. In the last case, on the other hand, the variance of RwoI indegree for the LPTs that is greater than that for the HPTs. This indicates that the number of conversation moments that led to responding without information varied more among the LPTs than it did among the HPTs. That is, the variability in how teams did not respond to questions or issues during the conversation occurred more often in LPTs than HPTs. This converse result does strategically align with the previous results. The picture of team success is not only asking for information from your team, but that your team members need to respond with helpful information and if they do not, it can easily lead to poor performance. Overall, these differences demonstrate that not only is there more than one way for an HPT to communicate, but that the indications of a LPT are when less ideas or feedback is generated. Although these results appear intuitive, they are able to be empirically demonstrated with real teams in a naturalistic setting quantitatively via FCMs in assessing communication flow and content simultaneously.

In all but one of the cases of statistical differences in variance, the HPTs had the higher variance. With the HPTs having the higher variances, it indicates that despite there being less HPTs involved in this analysis, the HPTs tended to have more varied amounts of information sent from or received by a node. This provides support to the previous point that the difference between HPTs and LPTs might be found in the nodes relationships to each other rather than the amount of information they send or receive. The higher variance for certain SAs and metrics for HPTs is also understandable after having seen from the ICC test that HPTs are more heterogeneous, as that would account for the wider spread in data.

The qualitative analysis occurred after the quantitative analysis in an exploratory sequential mixed methods approach. In a pattern exclusive to HPTs, it is quite apparent in the qualitative analysis, that RwoI had no occurrence of indegree. Further exploration found *a posteriori* that if RwoI was introduced in the conversation (e.g., through an SA not considered in this analysis), it always positively influenced RI, RC, and/or RwI in HPTs. A positive influence indicates that the specific interaction was relevant, i.e., helped in the completion of the task. What an observer would see in this case is that if the person to answer a question did not provide information, a member of the team would further probe the question, or provide another answer with information to help move the project forward. This further supports the point that when a request was made, the HPTs were more likely to respond with information, thus, continuously advancing the project. These were both patterns that were not seen in LPTs which is one of the ways in which the communication patterns in HPTs and LPTs differ and explain these differences in their performance.

Next, looking at patterns exclusive to LPTs, it was seen that the biggest node (node with the highest value of centrality) was the NR node. Any interaction between the NR node and any other node is always negative regardless of indegree or outdegree. A negative influence means that the specific interaction was not relevant, i.e., did not help in completing the task. This demonstrates that NR had the strongest influence (or impact) on the entire conversation and this influence was always negative in LPTs. In other words, the LPTs overwhelmingly had irrelevant or unproductive conversations which often led to non-responses, and unlike with the HPTs, these NRs were not further explored in the LPTs' conversations. Since these results show what is happening within the conversation, it might be difficult to explain how one would witness a negative influence. Likely, to an observer, this negative influence would be seen as silence from members of the team after a team member asks a question or makes a statement that requires a team member's response. Another way to look at this is that, the more non-responses were in the conversation, the less questions that were asked which led to less responses being made. In reality, it can be extrapolated and understood that non-responses in team discussions stifles communication and performance.

The results of the ratios examined continued this trend of stifling communication in LPTs. When the ratio of RwI indegree to the RI outdegree was greater than 1, it indicates that more information was provided to the team than was requested. All the HPTs had a ratio greater than 1 while not all LPTs did, demonstrating that HPT teams not only answered questions more than LPTs but communicated additional information that directly contributed to the success of the team. Theoretically speaking, adding the RC to the denominator of this ratio will only make them smaller. Yet, with the addition of RC, the HPTs on average still respond to requests more often than LPTs, but only by about 5%. These results in conjunction with the results of the qualitative analysis show marked differences between the LPTs and HPTs' communication patterns through FCM mapping. They highlight those differences in communication patterns leading to understanding the divergence in performance.

LIMITATIONS & FUTURE WORK

The trajectory of this work was to understand how team communication can be interpreted for flow and content using FCMs. Due to the originality of this work based on the standardized methodology and ability to visualize multidimensional aspects of communication in a singular image, there were indeed limitations that can inspire significant future work. The first limitation is the sample size of the teams. Although only 10 teams were analyzed, this produced a total of 5,183 utterances and 13,992 words communicated between team members. Teams ranged from 318 to 836 utterances, and from 660 to 2,100 words. Despite this, oversampling the tails with more extreme teams would be recommended to see if FCMs can distinguish between these teams. Additionally, despite all the data found within these teams, more data is required along the entire performance spectrum. Finding a pattern of movement in metacognition via communication along this spectrum from lower performing to higher performing teams could potentially assist teams in improvement throughout time via word choice, answering teammates direct questions, etc. In this analysis, the performance of the teams were already known and the analysis carried out were confirmatory rather than exploratory. That is, rather than trying to see how this data can be separated into preconceived groups, it might be more beneficial for applications in other fields to instead let the data form groups and study what differentiates those groups.

The next limitation to this study, which turned out to be more of an issue than had been initially anticipated, was the choice of metrics used to compare the FCMs. The metrics used in this study were the most commonly used in describing the behavior of FCMs, but not the only ones that exist. This study only looked at the effect of indegree, outdegree, and centrality of the different nodes (speech acts). Using metrics beyond that (e.g., hierarchical index) could capture alternative differences between the maps not previously noted and provide a clearer image of what the LPTs did that might have been different from the HPTs. However, current research using FCMs does not compare multiple FCMs at either the individual or augmented levels. Comparisons are purposely avoided in the literature. The general process of avoidance is simply by aggregating the different FCMs into another, singular augmented FCM and interpreting that final FCM using the different metrics used in this research. Future research must examine the application of other metrics that might capture more or different information from the FCMs, as well as finding methods of comparing these FCMs that can be used more broadly and in communication.

CONCLUSION

This study explored whether or not FCMs can capture communication content and flow, simultaneously, while linking these patterns to team performance. Overall, the entire methodology, from the way the communication data was coded to the creation of the FCMs, provides evidence that FCMs can be used to study content and flow of team communication simultaneously. Content presents itself when coding the data based on the topics that were included. Flow of communication between people comes into play when creating the original one-on-one conversation FCMs. Additionally, the various FCMs produced can also provide different levels of information, such as within team dynamic (the individual FCMs) and between team dynamic (the aggregated FCMs). Furthermore, this research shows that flow of content can be analyzed using this method as well. As a matter of fact, the majority of the analysis was performed on the flow of content within and between the teams. Both content and flow of the FCMs can be studied, as well as flow of content, to expand research in team communication and performance.

In summary, both questions this research set out to answer were supported. Communication patterns similarities can indeed be seen using FCMs (*Question 1*). However, FCMs alone are not sufficient and various statistical methods were applied to their outputs for a holistic perspective of the team communication data. Likewise, FCMs do capture and differentiate the different communication patterns at opposing ends of the performance spectrum (*Question 2*). These differences, however, cannot be seen without prior knowledge of team performance, at this time. In this research, the high and low performing teams were already known. Examination and analysis of different metrics and methods are required for future work to be predictive with respect to team performance and potential communication traps that could lead to poor team performance.

This research has the ability to fill in a significant gap in the study of team communication. Ultimately, this research shows that there appears to be multiple communication patterns that lead to high performance, whereas one particular communication pattern that leads to low performance. Future interest may not be in just coaching team members what to do for success, but rather, to inform them of what not to do. FCMs were able to indicate patterns that should be avoided in low-performance teams rather than demonstrating a singular team communication pattern aiming for high-performance teams. Therefore, with further research into different metrics and expansions of this work, this method can be used to identify pitfalls in communication for teams to avoid in order to achieve the best team performance possible. Expansions of this work by overlapping understandings in communication with other various aspects of team dynamics (e.g., personality, team cohesion) in order to help identify who works best with whom could ultimately, lead to the formation of more effective and productive teams.

REFERENCES

Allen, T. J. (1966). Studies of the problem-solving process in engineering design. *IEEE Transactions on Engineering Management, EM-13*(2), 72-83. doi: 10.1109/tem.1966.6447087.

Allen, T. J. (1977). *Managing the flow of technology*. Cambridge, Mass.: Massachusetts Institute of Technology.

Berkes, F., & Berkes, M. (2009). Ecological complexity, fuzzy logic, and holism in indigenous knowledge. *Futures, 41*(1), 6-12. doi: 10.1016/j.futures.2008.07.003

Bliese, P. D. (2000). Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. In K. J. Klein, & S. W. J. Kozlowski (Eds.), *Multilevel Theory, Research, and Methods in Organizations* (349–381). San Francisco: Jossey-Bass.

Bowers, C. A., Jentsch, F., Salas, E., & Braun C. C. (1998). Analyzing communication sequences for team training needs assessment. *Human Factors*, *40*(4), 672-679.

Brown, M. B., & Forsythe, A. B. (1974). Robust tests for the equality of variances. *Journal of the American Statistical Association*.

Clark, H. H., & Brennan, S. E. (1991). Grounding in communication. In L. B. Resnick, J. Levine and S. D. Teasley (Eds.), *Perspectives on Socially Shared Cognition* (127-149). Washington, DC.: American Psychological Association.

Cooke, N. J., Duchon A., Gorman, J. C., Keyton, J., & Miller, A. (2012). Preface to the special section on methods for the analysis of communication. *Human Factors*, *54*(4)*,* 485-488, Aug. 2012.

Creswell, J. (2014). *Research Design: Qualitative, Quantitative and Mixed Methods Approaches,* 4 (220-231). Thousand Oaks: SAGE Publications.

Driskell, J. E., Hogan, R., and Salas, E. (1987). Personality and group performance. In C. Hendrick (Ed.), *Review of personality and social psychology*, 9 (91–112). Newbury Park, CA: Sage

Gorman, J. C. (2013). The concept of long memory for assessing the global effects of augmented team cognition. *Proceedings of Human Computer Interaction (HCI) International,* 22-27.

Gorman, J. C., Cooke, N. J., Amazeen, P. G., & Fouse S. (2012). Measuring patterns in team interaction sequences using a discrete recurrence approach. *Human Factors*, *54*(4) 503-517.

James, L. R. (1982). Aggregation bias in estimates of perceptual agreement. *Journal of Applied Psychology*, 67 , 219-229.

Khawaja, M. A., Chen, F., & Marcus, N. (2012). Analysis of collaborative communication for linguistic cues of cognitive load. *Human Factors*, *54*(4), 518-529.

Kim, J. H., Macht, G. A., & Li, S. (2012). Comparison of individual and team-based dynamic decision-making task (anti-air warfare coordinator): Consideration of subjective mental workload and metacognition. *Proceedings of the Human Factors and Ergonomics Society (HFES) Annual Meeting, 56*(1), 2517-2521.

Kim, J. H., Macht, G. A., Rothrock, L., & Nembhard, D. A. (2014). Developing metacognitive model for team-based dynamic environment using fuzzy cognitive mapping. *2014 Proceedings of Human Computer Interaction (HCI) International*, 325-334.

Kim, J. H., Rothrock, L., & Tharanathan, A. (2016). Applying Fuzzy Linear Regression to Understand Metacognitive Judgments in a Human-in-the-Loop Simulation Environment. *IEEE Transactions on Human-Machine Systems*, *46*(3), 360-369.

Kirkman, B., Tesluk, P., & Rosen, B. (2004). The Impact of Demographic Heterogeneity and Team Leader-Team Member Demographic Fit on Team Empowerment and Effectiveness. *Group & Organization Management*, *29*(3), 334-368. doi: 10.1177/1059601103257412

Kosko, B. (1986). Fuzzy cognitive maps. *International Journal for Man-Machine Studies, 24*(1), 65-75.

Kosko, B. (1996). *Fuzzy engineering*. Upper Saddle River, NJ: Prentice Hall.

Kwasitsu, L. (2003). Information-seeking behavior of design, process, and manufacturing engineers. *Library and Information Science Research, 25*(4), 459-476.

León, M., Rodriguez, C., García, M.M., Bello, R., Vanhoof, K. (2010) Fuzzy Cognitive Maps for Modeling Complex Systems. In: Sidorov G., Hernández Aguirre A., Reyes García C.A. (eds) *Advances in Artificial Intelligence*. MICAI 2010. Lecture Notes in Computer Science, vol 6437. Springer, Berlin, Heidelberg

Levene, H. (1960). In *Contributions to Probability and Statistics: Essays in Honor of Harold Hotelling, I. Olkin [and others], etc*. Stanford: Stanford University Press, 278-292

Lonergan, J. M., Long, H. J., Bolin, A. U., and Neuman, G. A. (2000). The Big Five, Task Type and Group Performance: A Meta-Analysis. *Presented at the 15th Annual Meeting of the Society for Industrial and Organizational Psychology*, New Orleans, Louisiana, April 14–16.

Macht, G. A. (2014). *Modeling psychometrics for team performance: Personality & emotional intelligence*. (Doctoral dissertation). Pennsylvania State University, University Park, PA.

Marks, M. A., Mathieu, J. E., & Zaccaro, S. J. (2001). A temporally based framework and taxonomy of team process. *Academy of Management Review*, *26*(3), 356-376.

Mohammed, S., & Angell, L. (2004). Surface- and deep-level diversity in workgroups: examining the moderating effects of team orientation and team process on relationship conflict. *Journal Of Organizational Behavior*, *25*(8), 1015-1039. doi: 10.1002/job.293

Patrashkova-Volzdoska, R. R., McComb, S. A., Green, S. G., & Compton, W. D. (2003). Examining a curvilinear relationship between communication frequency and team performance in cross-functional project teams. *IEEE Transactions on Engineering Management, 50*(3), 262-269.

Poole, M. S. (1999). In L. R. Frey (Ed.), *The Handbook of Group Communication Theory and Research*. SAGE Publications: Thousand Oaks, CA. 37-71.

Rehim, S., DeMoor, S., Olmsted, R., Dent, D., & Parker-Raley, J. (2017). Tools for Assessment of Communication Skills of Hospital Action Teams: A Systematic Review. *Journal Of Surgical Education*, *74*(2), 341-351. doi: 10.1016/j.jsurg.2016.09.008

Shannon, C. E., & Weaver W. (1949). *A Mathematical Model of Communication*. Urbana: University of Illinois Press.

Shrout, P. E., & Fleiss, J. L. (1979). Intraclass Correlations: Uses in assessing rater reliability. *Psychological Bulletin*, 86, 420-428.

Stevens, R. H., Galloway R. L., Wang P., & Berka C. (2012). Cognitive Neurophysiologic Synchronies: what can they contribute to the study of teamwork?. *Human Factors*, *54*(4), 489-502.

Stewart, G. (2006). A Meta-Analytic Review of Relationships Between Team Design Features and Team Performance. *Journal Of Management*, *32*(1), 29-55. doi: 10.1177/0149206305277792

Stylios, C. D., Georgopoulos V. C., Malandraki G. A., & Chouliara S. (2008). Fuzzy cognitive map architectures for medical decision support systems. *Applied Soft Computing, 8*(3), 1243-1251.

Wang, P.P., Chang S.K. (1980) Fuzzy Sets: Theory of Applications to Policy Analysis and Information Systems. In Wang P.P., Chang S.K. (eds) *Fuzzy Sets*. Springer, Boston, MA.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338-353.