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ANALYSIS OF VIRTUAL COMMUNICATION WITHIN ENGINEERING DESIGN TEAMS AND ITS IMPACT ON TEAM EFFECTIVENESS

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ABSTRACT

Online communication and collaboration tools are changing the way teams design products. The tools also generate a rich data source from which to study trends in communication. This paper focuses on how engineering teams utilize Slack, a popular team messaging software platform. We aim to better understand communication and coordination in product design teams via analysis of team social network dynamics, unique patterns of chat-like messaging (emoji usage), and the evolution of communication topics over time.

Our study analyzes the online interactions of 32 teams, sent during a 3-month senior undergraduate product design course. These 400,000+ messages represent the team communications from 4 years of teams, with 17-20 students per team.

We find that 1) Slack communications resulted in high density network maps, 2) network analysis of teams reveals that leaders have more central positions in the network, 3) strong teams have lower average centrality among members, equivalent to less public channel membership per person, 4) stronger teams use emojis at a higher rate, and 5) emojis are used most by leaders and highly connected members.

These findings represent preliminary foundations for best practices in online messaging, which may lead to more effective collaboration in product design.

1. INTRODUCTION

Communication, key to the engineering design process, is being disrupted by new technological developments changing the ways by which teams collaborate in the classroom and the workplace. Teams worldwide are adopting online communication software for information sharing, documentation, project management, collaboration, and decision making. Slack, an online message-based communication software, has become a staple tool for student and industry engineers alike, with tens of millions of users [1]. Slack not only facilitates team messaging, but also supports a variety of project management and external integrations [2]. These software platforms unlock data for quantitative analysis of design team communication and collaboration, from which we can identify patterns of virtual communication content, timing, and organization.

Previous studies have analyzed email communication of engineering teams [3], or the use of Slack by software development teams [4,5] and Information Technology enterprises [6]. This paper focuses on student product design teams, building on previous work [7]. We analyze 400,000+ virtual interactions sent by 32 different teams over the span of three months, as they progress through the stages of product design, from ideation to alpha prototype launch.

We explore the intricacies of the individual contributions and dynamics within teams through network analysis, emoji frequency analysis, and topic modelling of electronic communications. Each team, having unique communication patterns, is anticipated to have distinct network connectivity among team members. It is hypothesized that these differences will be driven by individuals' roles within the team structure. Furthermore, high connectivity, defined by mutual membership in a communication channel, is expected to be a predictor of team effectiveness. It is anticipated that the effectiveness of team communication will be demonstrated by successful teams communicating more topics in fewer messages. To facilitate nonverbal communication, use of emoji 'reactions' is predicted to correlate with stronger performance.

The insights gained from this paper will provide a better understanding of how to optimize engineering design, communication, and collaboration. Learnings will provide clarity as to the conditions which influence technology-enhanced teams and their members to perform most effectively. By improving the experience, outcome and education of engineers designing collaboratively, the research will enhance our ability to meet the demands of the changing labour market, whereby creativity and interpersonal skills are increasingly valued.

1.2 Literature Review

1.2.1 Team Communication

Team communication is characterized as information exchange, both verbal and nonverbal, between two or more team members [8,9]. Team communication is conceptualized as integral to a majority of team processes or the interdependent team behaviours that lead to outcomes, such as performance [10]. Common across studies of team effectiveness is the ability of high performing teams to effectively communicate, as compared to lower performing teams [11]. It has been found that communication is positively correlated with team success [9], and that quality of communication is a greater predictor of team success than frequency of communication [12].

1.2.2 Modes of Communication

More specific to the present study is the medium of communication. As defined by Gibson & Cohon, virtual teams have the following three characteristics: members who are working towards a common goal, geographically dispersed members, and reliance upon technology-mediated communications rather than face-to-face interaction [13,14]. Virtuality, a measure of how much of a team's communication is virtual, is conceptualized as a continuum, ranging from virtual to offline communications, a function of dependence on electronics and degree of geographical dispersion [13]. Teams with both virtual and face-to-face communication are referred to as hybrid [15]. Anticipated disadvantages of virtual modes of communication include less shared understanding and absence of nonverbal communication, leading to misinterpretation and misunderstanding [13]. Recent studies have found that, while online messaging platforms promote transparency and team awareness, they can also result in excessive communication and unbalanced activity among team members [5]. Particularly, preliminary analysis on this paper's dataset by Van de Zande found that successful teams have more consistent and organized communication patterns, while also having lower quantities of messages [7].

1.2.3 Injecting Nonverbal Communications to Digital Media

A major concern of virtual communication includes the lack of nonverbal cues that are typically present in face-to-face communication [13]. Psychological studies show that over 65% of information exchange in face-to-face interactions is nonverbal, in the form of facial expressions, body language, and hand gestures [16]. In digital networks, virtual embodiments of varying fidelity have been shown to enhance communication [17]. A low fidelity and widespread application of nonverbal communication is the emoji (also referred to as ideogram or smiley), to complement and even replace text [18].

Virtual communication not only makes it difficult for humans, but also machines, to decipher emotion. Sentiment analysis through text alone has proven a difficult problem for natural language processing [19]. However, with illustrated faces, objects and symbols, this deciphering becomes much easier. One study shows that a Tweet's sentiment generally agrees with that of the emoji(s) embedded [20].

Slack presents the ability to 'react' to messages with a set of standard emojis, and the added functionality to upload custom images as emojis [2]. The dataset therefore presents the opportunity to explore which emojis are used most frequently, and how frequency of emojis sent and received differ by team role. For example, we might expect team leaders to send more emoji reactions as a means of demonstrating engagement with the team, or in an attempt to establish a culture of acknowledgement. We may expect the messages of team leaders to receive more emoji reactions, indicating the use of emoji reactions as team coordination or consensus building. Overall, teams with more emoji engagement are expected to be more effective, demonstrating the added benefit of nonverbal communication.

1.2.4 Communication Networks in Engineering Design

Efficient and effective communication is essential to the productivity of research and development teams [21]. A powerful tool for analyzing communication is network analysis [22], which is frequently visualized using network connectivity graphs. These graphs are constructed by each individual (or role) represented by a node, with edge weights corresponding to some measure of interaction (for example mutual activity participation [23]). The constructed graphs represent communication patterns, with individuals' position in the network conveying centrality and influence.

From this network data structure, we can also extract key graph measures, at both the system and node level. Closeness centrality – the inverse of the summed distance to all other nodes – has been linked to Research and Development times within organizations [24]. Individuals with greater closeness have more direct access to information from individuals throughout the network. Eigenvector centrality calculates the eigen equation, $\lambda v = Av$, whereby A is the adjacency matrix of the network, to find clusters of neighbouring nodes with the highest connectivity among the network [25]. This helps to identify groups of influence. Degree centrality, defined by the number of connections incident upon a node, represents immediate influence of a given individual within a design team, as higher degree indicates greater amount of incident information flow [25]. Effective managers who are regarded as leaders by their team have been found to be those with higher centrality and influence in the network [26]. Density is the ratio of network connections to all possible connections between nodes, whereby a fully connected graph has density of 1. When considering a product development team, previous studies have suggested that higher density increases knowledge sharing, but can hinder progress [25].

We expect to see a pattern of high density, close to 1, in the team data. We anticipate more successful teams to have a smaller range in connectivity across members. On the individual-level, we expect to see the embeddedness of team leaders to be reflected in their high level of centrality relative to the rest of the team.

1.2.5 Topics in Engineering Design

Engineering design projects progress through a series of phases, from ideation to launch [27]. Online communications represent an increasing amount of engineering design work, with email representing 14% of design work itself [28,29]. Team communications, therefore, are likely to change over time, indicating timely priorities and focus. Topic modeling is a technique used to analyze large datasets to identify particular topics present in text. This technique has been previously used to analyze the subjects of the email corpus of a large engineering design project of a power plant [30], revealing the progress of topics over the project lifecycle in three phases: conceptual design, detailed design, and commissioning. In this case, topics from emails were found to often represent design problems and rework. It is also possible to leverage topic modeling as a means of monitoring engineering design projects [3]. Again, via analysis of project emails, the authors present patterns in the dynamics of topic activity over time, contributing to the early collection of product design project topic analysis. The authors measure topic frequency of occurrence and occurrence duration. The study found that many topics are not "stage-bound," meaning they are relevant throughout the life of the project, not simply in one of the design process stages.

These studies suggest that we might find technical topics, representing challenges and problems, or process steps like meetings and logistics. Through exploratory study of topic analysis through the phases of the design process, we may reveal the key priorities of teams.

The breadth of topics, represented by a conversational word base, is an indicator of conversational progress and complexity [31]. Topic breadth is anticipated to have an increasing trend throughout project progression, indicating the increased detail and specificity of team discussion. However, dips in topic breadth and word base may be expected during stages in which teams are converging on ideas. Overall, effective communication may be demonstrated by more successful teams covering more topics in the same amount of messages.

2. METHODS

2.1 Dataset

The dataset to be analyzed is data from 32 teams' Slack messages from a fourth-year engineering design course.

2.1.1 Design Course Setup

The basis of this analysis is four years of a senior year core product design course in Mechanical Engineering at a major U.S. Institution. This particular course is an ideal baseline for data analysis because it represents a condensed yet complete design cycle, from research and ideation through to a viable alpha-prototype demonstration within three months. Product opportunities are identified by the student teams, with loose connection to an overall course theme each year. While topics vary depending on the student-identified opportunities, the course, deliverables, and timelines are controlled by the course staff through the course objectives.

The course setup mirrors real-world design conditions, and the sample contains a diverse mix of student demographics. Teams meet regularly in-person for labs, lectures and self-organized meetings, supplemented by Slack conversations. With respect to virtuality, these are hybrid teams of which only online communications will be analyzed. Each team is composed of 17-20 students [32].

The work is distributed amongst members of the teams, with only a few team roles imposed by the course structure itself. Those of interest to this paper are described in section 2.1.3.

2.1.2 Slack Messages

400,000+ Slack interactions from 32 student teams, over four distinct years of course delivery were analyzed. Slack data from all public channels were exported. Direct messages and private channels were not included in this dataset. The exported data include: user, channel, and message content information. Users each have distinct, randomized usernames. Messages are sorted by channel, then date, and have precise timestamps. All exported Slack data are provided in standard JSON format, but were converted to a relational SQL database for efficiency. This data collection was approved by the institutional review board.

2.1.3 Individual-level Characteristics

The communication data are supplemented by qualitative self-identification surveys. Members of Slack channels included instructors, mentors, and students; these distinctions were made to distinguish team members from auxiliary members. Analysis within our study will focus solely on interactions among primary (student) design team members. Within the team, students' specified roles were recorded. In particular, the role of interest is that of "System Integrator." Each team appoints two System Integrators, whose roles are to "assume a number of coordination and integration functions during the project, from both a project management and technical design viewpoint" [32].

2.1.4 Measures of Effectiveness

Expert ratings of each team's performance were derived from process and product success, based on instructor observation combined with various assessments. Based on this evidence, one expert judge sorted teams by performance into a dichotomous variable: stronger or weaker. This distinction was aggregated from the duration of the project through observation of team meetings and evaluation of course deliverables. While the author team acknowledges this metric for success has limitations, this metric was determined to be more holistic than grades alone. The dichotomous rating represents an effort to avoid the potential subjectivity of a scalar measure. This rating system will be used to distinguish communication characteristics of strong and weak teams.

2.2 Analysis

Three distinct forms of analysis were performed on the data.

2.2.1 Network Analysis

Having each individual represented by a node, graphs were constructed per team based on communication patterns, with edge weights corresponding to communication links. Given the data collected are composed of public channels, communication links were conceptualized as mutual membership of these channels. Edges were constructed based on this condition of mutual membership. The number of channels that two nodes had in common corresponded to the weight of the edge connecting these two nodes. Each team's network graph only included relevant student team members, excluding auxiliary members of the Slack team, such as mentors, bots, and students who dropped the course.

Measures of connectivity were calculated for the graph and individual nodes. Graph measures include density and average degree connectivity. Individual measures calculated were degree centrality, closeness centrality, and eigenvector centrality.

2.2.2 Emoji Reaction Analysis

Data of emoji reactions were analyzed for both team and individual contributors. The total number of reactions per team was calculated. To eliminate the bias of message frequency, proportionality of emoji reactions to total communications was measured. The most popular emoji reactions per team were counted and ranked.

On an individual contributor level, the number of reactions both sent and received were analyzed. These were then compared to the total number of reactions shared among a team. Individual analyzes were aggregated based on role. We tested for differences in emoji communication patterns by role using a two-sample t-test.

Results from network analysis were used to draw a connection between connectivity and communication frequency. Linear regressions were performed to determine the relationship between an individual's relative connectivity and: messages sent, emojis sent, emojis received and total team interactions.

2.2.3 Topic Modelling

Natural Language Processing (NLP) techniques were employed to reveal recognizable themes and reoccurring language. With input of messages, we tracked diversity of topics and extracted key topics throughout the product development process.

Preliminary analysis included bag-of-words implementation as an abstraction of topic diversity. This analysis was performed on: 1) the 'general' channel to gauge high level team topic conversations among teams, and 2) all channels to gain insight into overall team communications. A significant assumption made was that the general channel contained enough content to perform topic analysis. It was found that some teams used alternative self-created channels instead of general [7]. Each team's general channel, therefore, was identified as either the default #general or a self-created channel that included all team members and more activity than #general.

This analysis was performed on temporal windows corresponding to the discrete project stages and course deadlines, outlined in Figure 1. Each deadline was used as a separator between these windows, with the omission of "Final Selection." For each message sent within this window, the text was stripped of punctuation (aside from apostrophes), split into words separated by spaces, and lemmatized. Each word was added into a list, while stopwords and non-English words were eliminated. The number of unique words and frequency of the resulting words within this list were counted. The distribution of distinct words is a measure of the breadth of conversation, while highest frequency words are a good indicator of key topics. This analysis was also performed on all messages throughout the duration of the project to obtain aggregate topic information, which was used to normalize each team's results.

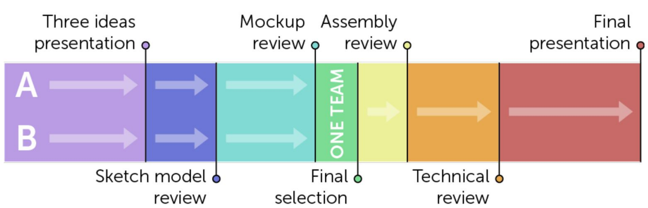


FIGURE 1: The scaled scheduling of deliverables for the course. All years follow a similar timeline, which is approximately 93 days long [7].

Secondary analysis included direct analysis using LDA (Latent Dirichlet Allocation) to extract key topics. This analysis was only performed on the 'general' channel to gain insights on the high level data, and to avoid bias from subsystems. Similar to bag-of-words, topic analysis was performed on distinct windows corresponding to project timelines. Each message sent within the given window was converted to a spaCy 'document' and lemmatized. The resulting set of documents were passed into the sklearn LDA model. The top five topics were extracted per team on each project stage.

3. RESULTS AND DISCUSSION

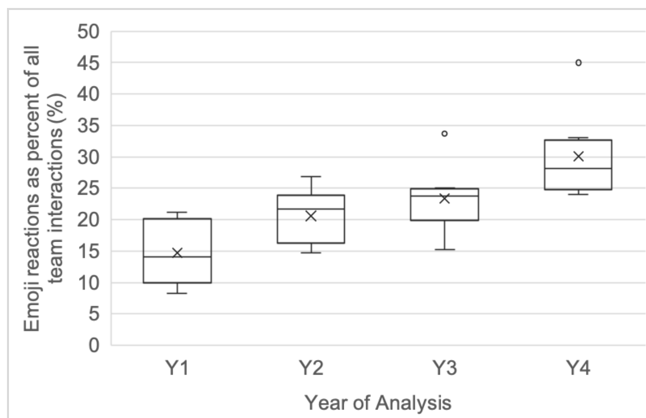
3.1 Emojis

3.1.1 Team Usage

All teams used emoji reactions as a significant portion of their communication. Among the teams, reactions made up 15-45% of all interactions. Emoji reactions are the primary form of nonverbal communication in Slack communications. The high usage of this feature confirms the significant role that nonverbal cues play in online communications.

Emoji usage is correlated with both year and strength of the team (Fig. 2). The team with the lowest usage was from Year 1 and classified as a 'weaker' team, while the team with the highest usage was from Year 4 and 'stronger'.

a)



b)

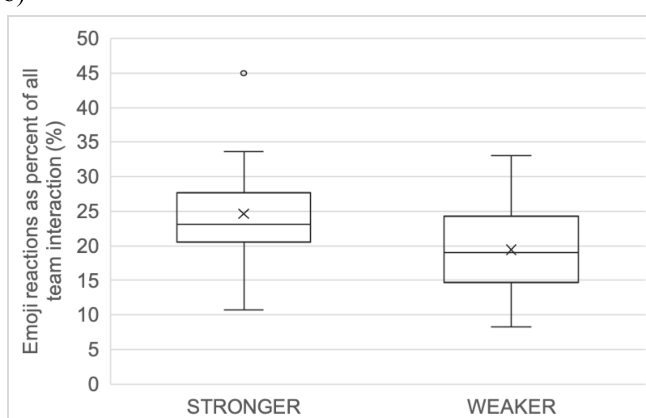


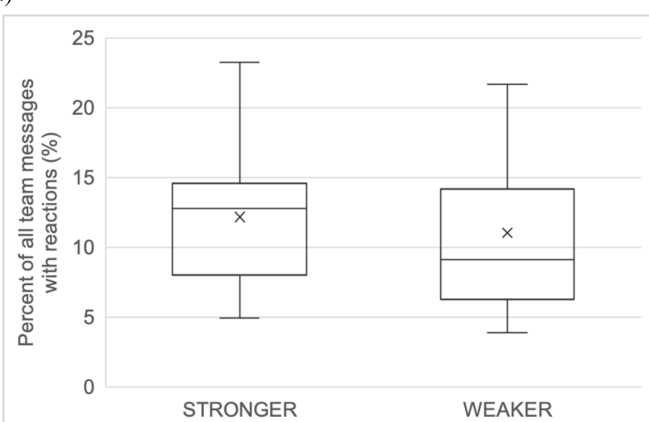
FIGURE 2: Boxplots of teams' emoji reactions as percent of total team interactions (messages, file sharing, reactions) classified by a) year and b) team performance. Enclosed box represents the 2nd and 3rd quartiles of the samples, line endings represent the 1st and 4th quartiles, dots are outliers, and 'x' is the sample mean.

The adoption of reaction usage increases over each successive year of the course. This is likely the result of increased adoption and familiarity. Many students use online messaging systems, including Slack, with emoji usage being a new addition to formalized settings of project management in school and work.

Stronger teams had higher usage of emojis with respect to all team interactions. Stronger teams used emojis as a greater percentage of all virtual communication (M = 24.6%, SD = 7.56%) than weaker teams (M = 19.4%, SD = 7.12%), (t(30) = 1.99, p <.1). This demonstrates the potential of emoji reactions as a medium for injecting nonverbal communication into virtual communications.

Furthermore, when analyzing the patterns of emoji usage on messages, both strong and weak teams have emoji reactions on the same percentage of messages, as seen in Figure 3a. However, as shown in Figure 3b, stronger teams have significantly more engagement on those messages with reactions (M = 2.8, SD = 0.46) than weaker teams (M = 2.3, SD = 0.30), (t(30) = 3.48, p <.01). This may be an indicator of positive behaviours, such as coordinated team input on messages or team cohesion.

a)



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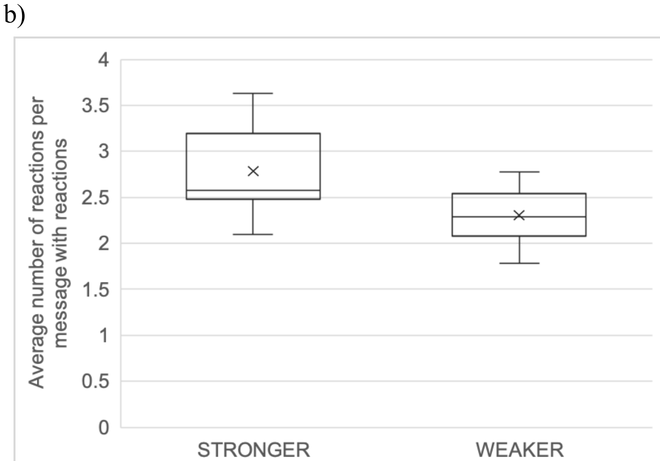
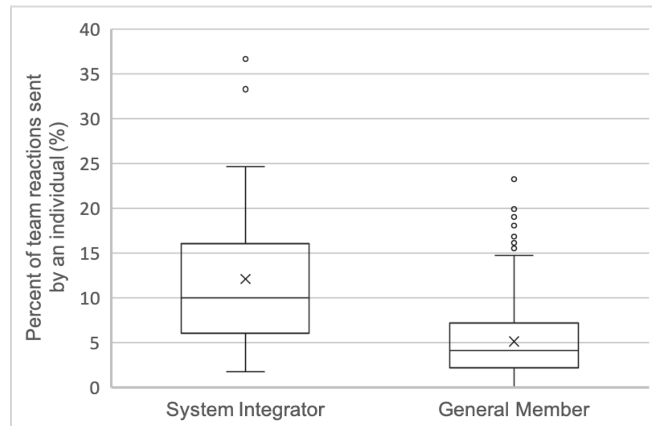


FIGURE 3: Boxplots for a) percent of messages with reactions and b) average engagement on messages with emojis, classified by team performance.

3.1.2 Differences by Role

Trends in emojis sent and received were further analyzed by team role, shown in Figure 4.

a)



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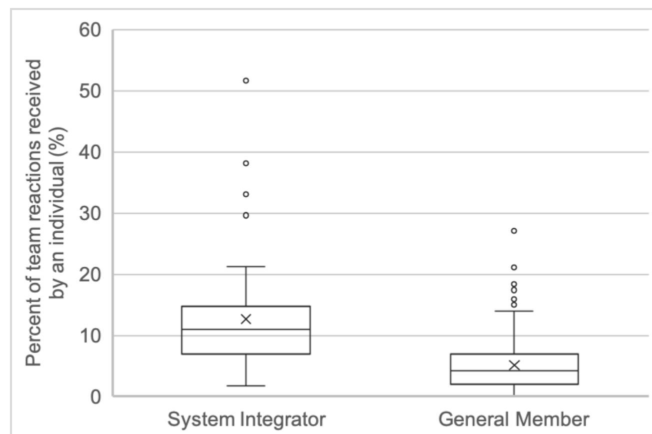


FIGURE 4: Boxplots of emoji reactions a) sent by and b) received by individuals as percentage of team's total emojis, grouped by System Integrators versus General Members.

A two-tailed t-test was performed on each dataset above to determine the statistical significance of the difference in emoji use by various roles. System Integrators sent more emojis (M = 12.1%, SD = 8.3%) than general members of the team (M = 5.1%, SD = 4.2%), (t(397) = 5.2, p <.001). Similarly, System Integrators received more emojis (M = 12.7%, SD = 9.5%) than general members of the team (M = 5.1%, SD = 4.0%), (t(397) = 4.9, p < .001).

This demonstrates that emoji reaction is a feature most used by System Integrators, the course's Project Managers. Given the role of a System Integrator, there are several ways in which reactions could provide value. Reactions could be sent to boost team morale and encourage others, while the receipt of reactions could indicate use of the feature as a simple poll for quick response.

3.1.3 Emoji Frequency

Next, we investigated the popularity of emojis by frequency of use, as summarized in Table 1. Each team's top five emojis were calculated. The occurrence of the most popular emojis were grouped and counted by image. Redundancy in skin tone variations and custom emojis meant that some teams had an emoji appear more than once within their top five.

TABLE 1: Most popular emojis across all 32 teams, based on teams' top 5 emojis

		Cumulative rankings of emojis (# of teams)				
Emoji Name	Image(s)	1st	2nd	3rd	4th	5th
Thumbs up (including skin tone variations)	👍 👍🏽	27	4	4	1	1
Colour heart corresponding to team colour	❤️ 💜 💚	4	7	6	2	-
Custom emoji relating to team colour	N/A	1	4	5	-	2
100	💯	-	4	2	-	1
Heart eyes	😍	-	3	1	3	1
Fire	🔥	-	3	2	2	1
Parrot (popularized custom moving emoji, and variations)	 	-	3	3	7	4
Standard heart	❤️	-	2	4	1	3
Other hand gestures	👌 👏 🙌	-	1	-	2	4
Custom emoji relating to course/team-mates/project)	N/A	-	-	2	7	6
Tears of joy/ laugh cry	😂	-	-	1	2	4

The "thumbs up" emoji (👍) is among the top three most popular emojis for all teams, and 84% of teams had it as the most popular. This suggests that the most popular use for the reaction feature is affirmation. Linking to real-world conversations, this would be equivalent to surveying nods and agreement around a table.

Furthermore, team names, which were colours (e.g. Blue Team, Orange Team, etc.), corresponded with many teams' top five emojis, as demonstrated by colour coordinated 'colour_heart' and other customized colour-related emoji reactions. Emojis can also elicit team bonding, with popularized custom emojis being an indicator of strong team identification and cohesion.

The lack of standard face emojis being among the top used emojis demonstrates that facial expressions are not a significant nonverbal communication achieved through reactions among these student design teams. All popular emojis have positive effects or connotations, reinforcing the belief that emojis are used for encouragement among design teams.

3.2 Network Analysis

3.2.1 Team Network Measures

Team communication networks were assembled with individuals as nodes and edges based on mutual channel membership. It was found that all of the networks were fully connected. Every team had a density of 1, meaning that every member had a direct link to every other member, through a public channel. Creating these maps without incorporating #general and #random channels, whereby everyone is a member by default, yielded the same result. This fully connected structure, illustrated by four examples in Figure 5, allows for more direct communication to wider audiences. Therefore, all communication can be described as a cohesive network, which facilitates transparency and coordination, and builds trust among team members.

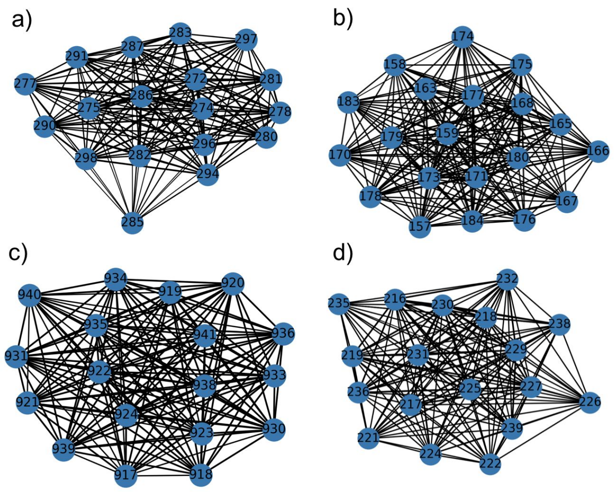


FIGURE 5: Network connectivity maps for four teams showing network patterns. Graphs b) and c) were stronger teams, and a) and d) were weaker teams. Numbered nodes represent anonymized user IDs.

Due to the lack of distinguishing features between the network maps, the structures as a whole could not be tested as a correlate to success. Instead, we further investigated the differences among individual nodes within the network.

3.2.2 Individual Network Measures

Due to the networks' highly connected nature, there were no meaningful differences in most standard network measures, such as betweenness centrality, and degree centrality, between individual nodes within graphs. As such, eigenvector centrality became the primary measure used to determine centrality of individual nodes in the team.

While not statistically significant at the 5% level, we can see in Figure 6 that stronger teams have less difference in centrality among team members. This shows that stronger teams have more equitable influence and involvement from members across the channels.

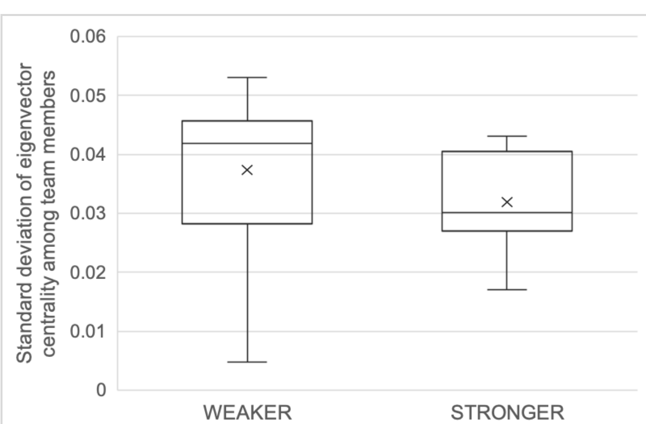


FIGURE 6: Boxplot of standard deviation of eigenvector centrality among team members, classified by team performance.

An unexpected result was that stronger teams had a lower average centrality, as illustrated in Figure 7. It was found that weaker teams had higher average centrality among members ($M = 0.24$, $SD = 0.006$) than stronger teams ($M = 0.23$, $SD = 0.005$) ($t(33) = 1.9$, $p < .01$). This could indicate that team members are oversubscribing to channels and ineffectively managing their online messages. As found in the literature, information overload is a downside of virtual communications, resulting in lower performance.

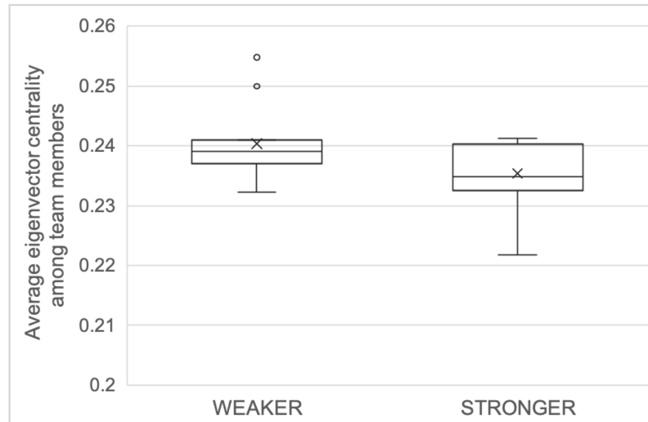


FIGURE 7: Boxplot of average eigenvector centrality among team members, classified by team performance.

As hypothesized, the most central members of the network were System Integrators, illustrated in Figure 8. System Integrators had a significantly higher eigenvector centrality ($M = 0.29$, $SD = 0.03$) than other members of the team ($M = 0.23$, $SD = 0.03$) ($t(263) = 8.3$, $p < .001$). System Integrators require high visibility across various aspects of the project, likely leading to their high connectivity.

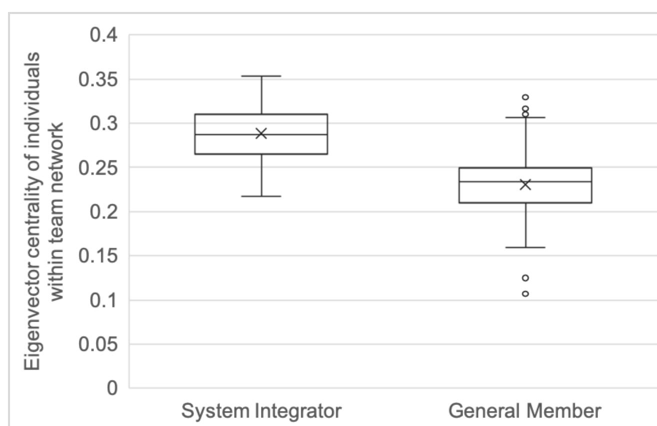


FIGURE 8: Boxplot of eigenvector centrality of individual team members within the network, grouped by System Integrator versus general member.

3.2.3 Centrality and Engagement

Given the relationship revealed with System Integrators having higher centrality and higher emoji engagement, these factors were combined in a linear regression analysis. Linear regression demonstrates whether these two variables are correlated across all team members.

The R^2 value for emoji reactions and messages, individually analyzed with eigenvector centrality, were low. Aggregating all interactions and assessing the correlation yielded a higher R^2 value of 0.4, as seen in Figure 9. This demonstrates that highly connected members were also those that engage most in online communications.

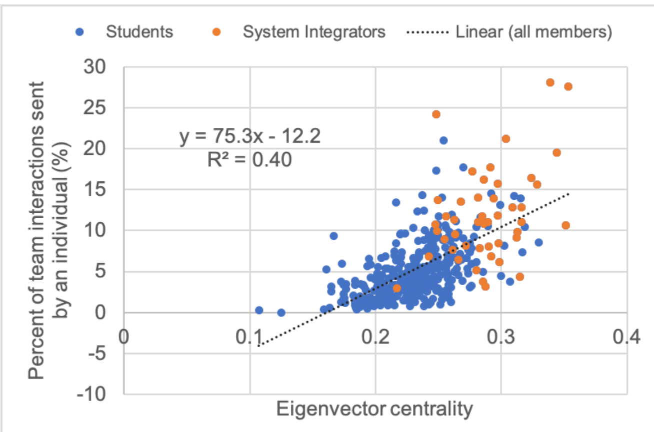


FIGURE 9: Relationship between individual's eigenvector centrality and percent contribution of all interactions within a network.

3.3 Topic Analysis

Topic analysis was performed on distinct project phases, summarized below in Table 2.

TABLE 2: Summary of project phases used for topic analysis.

	Phase Focus	Length (days)
Whole Process		93
Phase 1	Ideation	14
Phase 2	Sketch	10
Phase 3	Model	14
Phase 4	Assembly	14
Phase 5	Detailed Design	14
Phase 6	Alpha Prototype and Testing	27

3.3.1 Breadth of Topics over Time

Next, the breadth of topics (number of unique words) over the course of the project duration was explored. These results are illustrated in Figure 10.

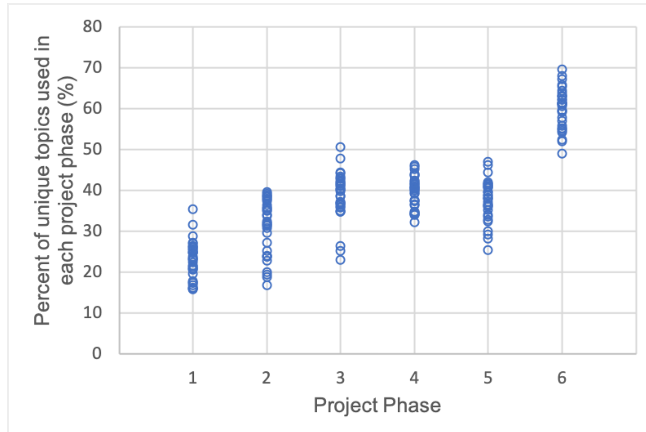


FIGURE 10: Percent of team's total unique words utilized during the six project phases.

The breadth of topic analysis over time shows an upward trend. This demonstrates the increased detail among channel conversations as the project progressed. Phase 6, the longest and last phase, had the most topics, as expected, while Phase 2, despite being the shortest, did not have the least topics. The summed percentage of all phase topics together, equal to approximately 240%, demonstrates the interdependence and overlap of topics between phases.

3.3.2 Topic Utilization of General

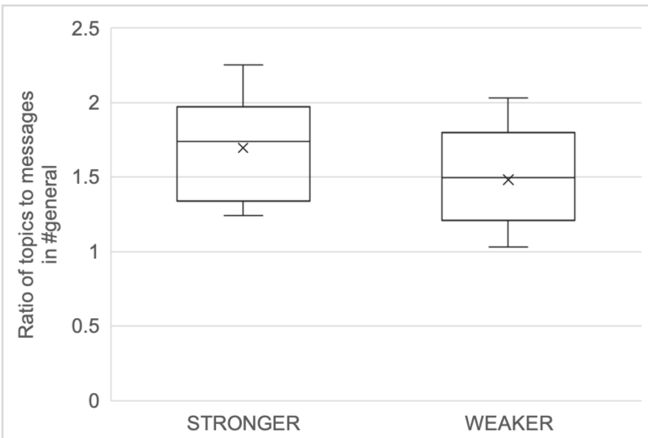
While the percentage of messages in the general channel (or #general) made up, on average, 16% of the messages in the team, the breadth of conversation of the general channel was 45% of that of the entire team Slack.

A key metric that arose from the bag-of-words analysis was the comparison of unique word count, or word base, to messages. This will be referred to as the word base to message ratio.

Within #general alone, all teams had a word base to message ratio between 1 and 2.6, which can be conceptualized as 1-3 unique words per message sent to the channel. This ratio for the full team Slack was in the range of 0.3-0.8. A high ratio indicates less repetition and more unique information sharing within a channel, and therefore demonstrates the use of #general as a summary of team updates and progress. It is anticipated that various subsystem channels likely contribute to the lower ratio observed when the team Slack is analyzed, as a whole. In particular, extensive discussions, product definition, and specification refinement could be contributing factors to word repetition.

Figure 11 shows the difference in word base to message ratio in weaker and stronger teams. A test of statistical difference did not find evidence of a significant difference in these ratios.

a)



b)

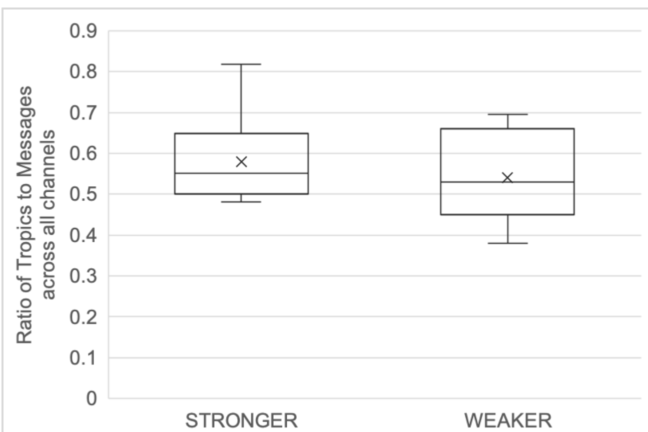


FIGURE 11: Boxplot comparison of the word base to message ratio for stronger and weaker teams within a) the #general channel and b) all team channels.

We can observe in Figure 11 that lower performing teams had a slightly lower word base to message ratio than high performing teams. This indicates that less effective teams used more messages to cover the same amount of topics, leading to more repetition and/or less efficient communication. Effective teams are slightly more concise in their communication, discussing more topics in fewer words.

3.3.3 Topic Progression

Exploratory analysis on the progression of topic analysis uncovered the dynamics of topic appearance over time. Topics tended to follow expected patterns based on the focus of design phases, i.e. the frequency of the topic "idea" in the early phases of design, as seen in Table 3. Those topics that were in the top 10 words used were noted.

TABLE 3: A representative team's significant topic progression over time.

	Phase of Design					
Topic	**1**	**2**	**3**	**4**	**5**	**6**
idea	■	■				
lab	■	■	■	■		■
change	■					
presentation	■	■	■			■
sketch	■					
model		■	■			
product			■			
user				■	■	
research				■		
code					■	
glass						■
test						■

Results for each individual team were aggregated to create Table 4. Topics presented were those common among most teams, and relate to the design process, as a whole. Most interesting among this data is the progression of how teams refer to the project's deliverable using the following terms: 'idea', 'product', 'prototype', and some project-defined name. Other key topics that were prevalent among all phases included: 'meeting', 'time', 'lab', 'team', 'channel'. These represented the more organizational aspects of virtual communication, used to coordinate meetings and work sessions.

TABLE 4: Aggregated key topics for all teams across project phases.

	Phase of Design					
Topic	**1**	**2**	**3**	**4**	**5**	**6**
idea	■	■				
poster	■					
presentation	■	■	■			■
research	■		■	■	■	
sketch	■	■				
decision		■				
model		■	■			
product			■	■		
user	■					■
implementation/ assembly				■	■	
prototype					■	■
test						■
project-specific					■	■

4 FUTURE WORK

Additional variables of interest at the individual-level, beyond leadership role, may reveal further patterns of team communication. For example, gender is known to influence communication tendencies [33,34].

Future work will replicate this analysis on data from industry design teams, seeking generalizability outside of the educational setting. Design teams may also be studied across various degrees of virtuality, with particular interest in fully virtual teams [13].

The current measure of team success is based on expert judgment, but a number of additional performance evaluations were executed through the course. Future work can explore sensitivity of the results to various measures of team success. Through a more extensive analysis of team success factors, we could expand upon these findings to develop a set of best practices for educational teams using online messaging platforms.

This paper presents preliminary analysis of message content. Future studies can use other Natural Language Processing techniques, beyond bag-of-words and LDA. Sentiment analysis could be employed to uncover individual behaviours and interpersonal dynamics of these virtual conversations.

Rich datasets pulled from online messaging platforms allow for new analytic techniques in the study of team communication. Beyond studying the correlation of communication patterns with team performance, the predictive power of these communication patterns could be tested against team performance outputs. Through machine learning techniques, models could be trained based on key metrics found in this work and other papers. The generalizability and accuracy of findings would be tested on external datasets. Such models could be implemented in virtual communication platforms to assess performance based on communication patterns. With realtime indication of their performance, teams can dynamically iterate upon their messaging structure and communication behaviours to improve project outcomes.

5 CONCLUSION

The online Slack repositories of design teams provide a rich dataset for engineering design researchers. This paper explores a series of methods for analysis of such data, and revealed a number of promising patterns of interest:

- Virtual messaging platforms like Slack enable highly connected networks through public channels, with the potential to promote transparency.
- Higher performing teams have a lower average in centrality among team members, equivalent to less public channel membership.
- Stronger teams use emojis at a higher rate than weaker teams.
- All teams have a similar proportion of messages with emojis, but stronger teams have more engagement on those messages with emojis.
- Emoji use and reception varies by role, and may help leaders to communicate nonverbal affirmation and facilitate team culture.
- More connected members have more communication interactions within a team.

The insights gained from this paper will provide a preliminary understanding of how to optimize engineering design, communication, and collaboration in hybrid teams.

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