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Development of a Communication Analysis System for Detecting Isolated Users in Slack

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Abstract

In recent years, various online communication tools such as Slack and Teams have been attracting attention. Unlike email, these tools have the advantage of reducing information oversight by enabling closed communication within an organization. Furthermore, they are more useful than email as they allow for easy messaging in a chat format and the ability to organize conversations by topic (a feature known as channels in Slack). Additionally, with the spread of remote work due to the COVID-19 pandemic, these tools have become increasingly utilized in many companies.

On the other hand, a drawback of online communication is that it becomes difficult to notice things that were visible in the workplace before. For example, employees who feel isolated and have trouble fitting into the organization could be discerned from their presence in the office or their expressions, but this is less visible online. Similarly, it's harder to gauge the atmosphere of teams that are not performing well. In this study, to address these issues caused by the emphasis on online communication, we designed and developed a system to analyze online communication histories. We defined indicators to identify isolated users and developed a system capable of analyzing and visualizing data from the widely used Slack. In this paper, we outline the system, discuss the results of organizational analysis using the system, and provide insights into future prospects.

Keywords: business chat data, network analysis, social isolation, social graph

1 Introduction

In recent years, the demand for remote work and online classes has increased due to the impact of the novel coronavirus infection (COVID-19). Consequently, communication in society has diversified, and video conferencing systems and chat communication systems

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have evolved. Especially, chat communication systems are still utilized today as alternatives or auxiliary systems for face-to-face communication. When conducting communication via text chat instead of face-to-face interaction, there are advantages such as no need to physically meet, ability to communicate regardless of location or time, and ease of file sharing. However, there are also drawbacks such as difficulty in understanding the other party's facial expressions, gestures, tone of voice, and their situation, which makes communication challenging. It is also difficult to understand the overall situation of the community, such as who is not participating in communication. Consequently, it is challenging to identify individuals who are not integrating into the community.

Isolation and loneliness in society have become significant issues[1]. The Minister of State at the Department of Health in Ireland has mentioned that loneliness is a serious problem for people's health. Health surveys indicate that isolation has significantly increased, and the proportion of the population with good mental health has decreased[2]. In response to this, various measures are being taken worldwide[3][4][5][6]. For example, in January 2018, the United Kingdom appointed a Minister for Loneliness. As part of their loneliness strategy, they have introduced the issue of loneliness into human relationship education in primary and secondary schools, and have incorporated a perspective on loneliness into various ministerial policies. Thus, isolation and loneliness are issues of global concern, and identifying isolated individuals is crucial.

Furthermore, the lack of communication among users affects the overall work engagement[7][1] and performance of the community, leading to negative impacts on the organization as a whole. This could result in decreased information sharing, lowered morale within the community, and worsened atmosphere. Moreover, individuals with diminished involvement in the community may struggle to adapt within their organizations, leading to increased stress from communication or feelings of exclusion within the organization, which could further impact job performance from a psychological standpoint.

Therefore, this study proposes a system to visualize organizational communication as a graph based on data such as messages and reactions in Slack, a chat communication system for organizations. The proposed system creates a graph representing the community using information obtained from Slack. The graph is created based on metrics such as the volume of communication and the number of reactions within the community, as detailed in Chapter 3.

The main advantages of creating graphs using the system proposed in this study can be summarized as follows: Firstly, by visualizing the connections within the community, the state of the community can be easily understood at a glance. The size of nodes in the graph represents the activity level within the community, and the edges indicate users with deep connections, making it easy to understand at a glance. Secondly, it allows for identifying users contributing to the activation of communication within the organization. Visualizing

[1] https://alone.ie/wp-content/uploads/2018/06/The-Loneliness-Taskforce-A-Connected-Island.pdf
[2] https://www.oireachtas.ie/en/debates/question/2024-01-23/573/
[3] https://www.redcross.org.uk/about-us/what-we-do/action-on-loneliness
[4] https://assets.publishing.service.gov.uk/media/5fb66cf98fa8f54aafb3c333/6.4882_DCMS_Loneliness_Strategy_web_Update_V2.pdf
[5] https://www.cao.go.jp/kodoku_koritsu/index.html
[6] https://www.myri.co.jp/publication/myilw/pdf/myri_no104_06.pdf
[7] Positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption.

the graph makes it easy to identify users who are deeply involved with many others within the community. Lastly, it facilitates the discovery of users with minimal communication within the community. This system enables the easy identification of such users at a glance.

The contributions of this study, provided by the above proposals, are as follows:

- By creating a community graph, organizational communication becomes easier to manage, and users with limited communication can be identified.
- Appropriate interventions can be implemented for identified isolated users, which can enhance overall work engagement and performance within the organization.

2 Related Work

In this chapter, we discuss relevant research related to our system, focusing on the impact of communication deficiencies within organizations and studies analyzing communication within organizations using chat data.

2.1 Impact of Communication Deficiencies within Organizations

Communication within organizations is crucial for people to integrate into the organization[2]. Factors such as psychological safety ("a shared belief among team members that the team is safe for interpersonal risk-taking")[3] and social support ("recognizing or experiencing being loved, valued, respected, or supported by others, or being part of reciprocal social networks of assistance or responsibility")[4] arising from such communication are considered significant factors that positively influence organizational performance, work engagement, and knowledge sharing[5]. It has been evident that social relationships and mutual understanding, including support from team members, empathy towards the team, and trust in team members, are essential to enhancing psychological safety and social support[6][7].

Various initiatives are being undertaken to address communication deficiencies within organizations. For instance, there are studies aimed at increasing communication frequency by developing applications to facilitate communication among new participants on Slack[8] and by reducing the physical distance between personnel within the organization[9]. As a preliminary step to such interventions, this study developed a system to identify isolated users with insufficient communication on Slack.

2.2 Communication Analysis within Organizations Using Chat Data

One notable study in communication analysis using organizational chat data is the analysis using email. Pawel et al. conducted analysis using approximately 640,000 email logs exchanged within a university institution[10]. They visualized the network structure of the organization based on the frequency of email replies. In this study, the researchers measured the frequency of communication between sender and recipient addresses recorded in emails, quantifying the level of communication activity for each employee.

Azarova et al. applied a similar network analysis method using email data to Slack, mapping message senders to message recipients and treating mentions in messages as corresponding recipients[11].

However, in online communication tools such as Slack, communities consist of multiple users organized into channels, where the default setting assigns all channel members as message recipients. Consequently, applying traditional email-based network analysis methods to online communication tools often results in a bias towards users belonging to numerous channels, leading to less useful outcomes.

To address this, Saito et al. proposed an analytical model that quantitatively expresses the relationships between users by focusing on the response intervals in conversation history data between two users on Slack[12]. They used a latent class model to visualize the relationship between the two users based on the message sender, recipient, and the intervals between their responses. They focused on the response intervals in messages between users, but these intervals depend not only on the users' communication characteristics and relationships but also significantly on their schedules for the day. Furthermore, they did not consider other information such as reactions and threads.

Therefore, in this study, we propose a new definition of contribution level and adjacency level for channel network construction, considering four types of information on Slack: message content, reaction data, mention data, and thread data, along with weights proportional to the size of each channel. We validate the discovery of isolated users and small-scale communities through network construction and visualization using this unique methodology.

Currently, commercial Slack analysis services such as NEWORG[8], COMCOM Analytics[9], and wellday[10] can estimate isolated users within an organization as well as estimate user work engagement and performance. Additionally, Slack's provided tool, the Slack Analytics Dashboard, visualizes the activity levels of each channel and member within the organization. However, none of these services provide a visualization of the overall organizational network, making it difficult to systematically grasp the structure. In contrast, the proposed system in this research visualizes communities through graphs, allowing for three main advantages to be easily obtained: understanding the community situation at a glance, discovering users who contribute to the activation of organizational communication, and identifying users with low communication levels.

3 Proposal System

In this study, we developed a system with the purpose of discovering isolated users using Slack. In this chapter, we describe the actual system architecture and the data used for analysis along with its processing methods. Firstly, we present the overall appearance of the system in Figure 1.

3.1 Data Collection Method

For creating the social graph, we utilized Slack provided by Salesforce. The reasons for choosing Slack include the availability of an API, the predominant use of Slack as the communication tool within our current research lab, and its popularity as the second most

[8] `https://neworg.laboratik.com`
[9] `https://analytics.comcom.app/lp`
[10] `https://wellday.jp`

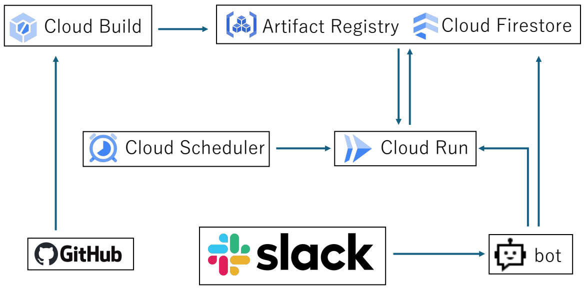

Figure 1: System Architecture Figure

Table 1: The data obtainable from the Slack API

Contained Information	Definition	Messages	Reactions	Mentions	Threads
userID	User ID of the user who sent the message	○	○	○	
channelID	Channel ID where the action occurred	○	○	○	○
targetUserID	User ID of the user who performed the action		○	○	
timestamp	UNIX timestamp	○		○	
targetTimestamp	UNIX timestamp of the message to which the reaction was sent		○		
threadTimestamp	UNIX timestamp when the thread was created				○
messages	Array representing other users' messages in the thread in the format of userId_timestamp				○
reaction	Type of reaction sent (String)		○		

commonly used business chat tool in Japan, following Teams[11]. The data obtained from the Slack API consists of messages, reactions, mentions, and threads. The data obtainable from the Slack API can be broadly classified into four categories: message sending information, reaction information, mention information, and thread information. The data included in each category is shown in Table 1.

For the purpose of data retrieval and management, GitHub[12] is used as the code management system, and the Slack API[13] is utilized to obtain organizational chat data. Subsequently, these data are managed by storing them in Google Cloud Platform's Cloud Firestore[14]. While the Slack Web API allows retrieval of message timestamps upon sending, it does not provide the timestamp for reactions. Therefore, by employing Slack's Events API and TypeScript, a system is used to save reactions to Cloud Firestore[15] in real-time when they are sent, enabling the acquisition of the precise timestamp for reactions.

3.2 Introduction of New Metrics

Utilizing this information, we introduce new metrics called contribution level and adjacency level.

[11] https://news.mynavi.jp/article/20221122-2518998/.
[12] `https://github.co.jp/`
[13] `https://api.slack.com/apis`
[14] `https://firebase.google.com/?hl=ja`
[15] `https://firebase.google.com/?hl=ja`

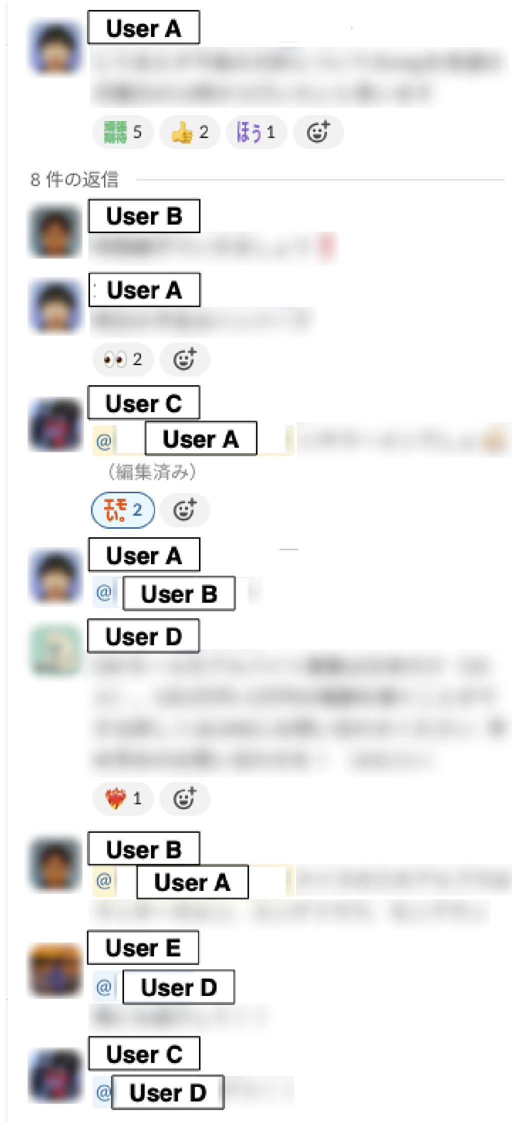

Figure 2: Example of communication on Slack

3.2.1 Contribution Level

The contribution level indicates the extent to which a user contributes to communication within the organization via Slack. The contribution level of a user is calculated as the sum of the number of messages sent and the number of reactions in public channels on Slack.

$$\text{Contribution Level} = \text{Number of Messages Sent} + \text{Number of Reactions} \tag{1}$$

A specific calculation example using the Figure 2 is presented. For user A, the contribution level is calculated as follows: with 3 messages sent and 4 reactions, user A's contribution level is 7. While this calculation is limited to one channel and one thread, users belong to multiple channels, so the total of all their message and reaction counts across all channels determines their contribution level.

Table 2: Adjacency Matrix calculated from the number of Messages sent in Threads

	UserA	UserB	UserC	UserD	UserE
UserA	0	5	5	4	4
UserB	5	0	4	3	3
UserC	5	4	0	3	3
UserD	4	3	3	0	2
UserE	4	3	3	2	0

3.2.2 Adjacency Level

The adjacency level indicates the strength of interaction between users on Slack. The adjacency level between users is calculated as the sum of four elements in public channels on Slack.

- Sum of posts by each user in threads
- Number of reactions to others' messages
- Mention Messages
- Channel Posts

A specific calculation example using the Figure 2 is provided.

1. Sum of posts by each user in threads

   First, the total number of posts by each user in threads is calculated, resulting in a matrix as shown in the Table 2. For the adjacency level between users A and B, where user A has 3 posts and user B has 2 posts in the thread, their adjacency level is $2+3=5$.

2. Number of reactions to others' messages

   Next, the number of reactions to others' messages is calculated, resulting in a matrix as shown in the Table 3. The adjacency level using the number of reactions to others' messages is calculated from the sum of a user's reactions to others' messages and reactions to their own messages from others. For example, in the given thread, user A has reacted once to messages from users C. User C has reacted 3 times to user A's messages, while users B, D, and E have reacted 2, 2, and 0 times, respectively. Therefore, the adjacency level between users A and B is $0+2=2$, and between users A and C is $1+3=4$. Although the explanation focused on user A, similar calculations are performed for each user to compute the adjacency level among all users.

3. Mention Messages

   Next, the adjacency level through mention messages is calculated. When a mention message is sent, the adjacency level between the user who sent the mention message and the user mentioned is increased by 1. If the mention message mentions all users in the channel ("@channel"), no increase in adjacency level occurs. For instance, focusing on user A in the Figure 2, user A sent 1 mention message to user D, and

Table 3: Adjacency Matrix calculated from the number of Reactions to other users' Messages

	UserA	UserB	UserC	UserD	UserE
UserA	0	2	4	2	0
UserB	2	0	1	0	0
UserC	4	1	0	2	0
UserD	2	0	2	0	0
UserE	0	0	0	0	0

user B sent 1 mention message, while users C, D, and E sent 1, 0, and 0 mention message to user A, resulting in the following adjacency levels between user A and users B, C, D, and E.

(UserA, UserB)=$0+1=1$,
(UserA, UserC)=$0+1=1$,
(UserA, UserD)=$1+0=1$,
(UserA, UserE)=$0+0=0$,

4. Channel Posts

   Finally, the adjacency level through channel posts is calculated. When a user sends a message in a channel, the adjacency level with other members in that channel is increased by a fraction of (the number of members in the channel - 1). The reason for dividing by the number of channel members is to mitigate the impact of large channels with many members, as messages in such channels are seen by many users but may not necessarily have strong individual relationships. Conversely, posts in channels with fewer members are considered to indicate deeper relationships among users within that channel. Therefore, the calculation method aims to assign higher adjacency level values to posts in channels with fewer members. For instance, focusing on user A's posts in the Figure 2, user A made 3 posts, and there are 14 members in the channel, so $3/(14-1)$ is added. Additionally, user B made 2 posts, while users C, D, and E made 2, 1, and 1 post, resulting in the following adjacency levels between user A and users B, C, D, and E.

   (UserA, UserB)=$3/13+2/13=5/13$,
   (UserA, UserC)=$3/13+2/13=5/13$,
   (UserA, UserD)=$3/13+1/13=4/13$,
   (UserA, UserE)=$3/13+1/13=4/13$,

3.3 Creation of Social Graph

Contribution level is represented by the size of nodes in the social graph, with larger nodes indicating higher contributions. Adjacency is represented by the distance between nodes, with closer distances indicating higher adjacency. Additionally, to enhance the visibility of the graph, nodes with contribution level that is too small are processed to a certain size. Similarly, for adjacency, to increase the visibility of the graph and the separability of clustering, adjacency values below a certain threshold are omitted. The social graph created in practice is described in Figure 3.

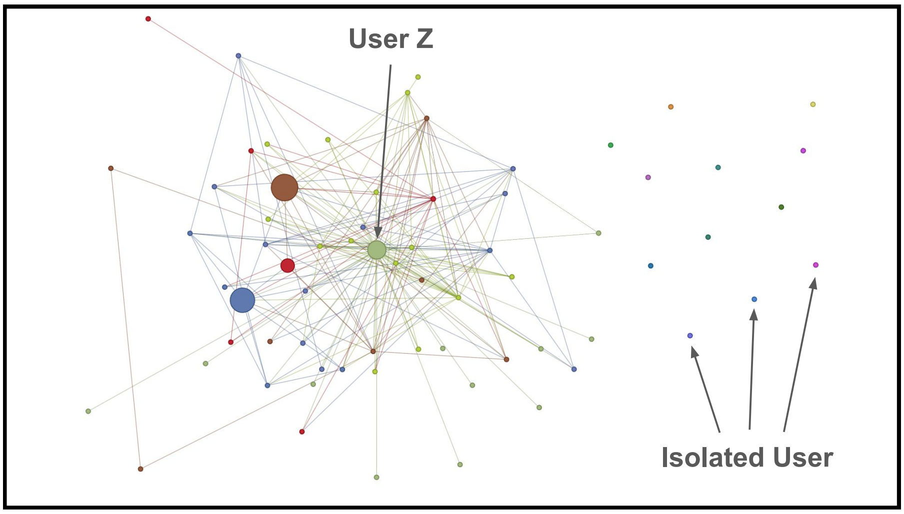

Figure 3: Social Gragh

4 Social Graph Analysis

In this chapter, we discuss analysis and discussions regarding the relationship between the results of the social graph visualizing communication relationships on Slack using contribution level and adjacency level, and several indicators. Figure 3 shows the social graph based on Slack data for May and June 2023 from the laboratory used in this analysis.

4.1 Clustering

The created social graph was clustered using the Louvain algorithm[13] to maximize the modularity metric, dividing the graph nodes into clusters based solely on adjacency level without considering contribution level. This algorithm first assigns each node to a different community in Phase 1. Then, each node is reviewed in turn, and the increase in modularity is evaluated if the node is moved to an adjacent community. The node is moved to the community where the increase is maximal. This process is repeated until no further improvement in modularity is expected. Next, the communities created in Phase 1 are consolidated into a single node, and a new network is constructed. The Phase 1 algorithm is then reapplied to this new network, repeating the process until no further improvement in modularity is expected.

As a result, the clustering categorized six groups with two or more members and twelve groups with one member, considering users in the latter as isolated users. With a total of 68 users, the proportion of isolated users was 18%.According to the Louvain algorithm, users identified as isolated have limited communication with others and exhibit a low degree of adjacency.

Furthermore, for the 6 groups obtained through clustering excluding isolated users, positive correlations were observed between contribution level and the message ratio in contribution level in four of these groups, as shown in Table 4.

The message ratio within the contribution level refers to the proportion of messages within the total contribution level calculated as the sum of message count and reaction

Table 4: Correlation between Contribution Level and Message Ratio by group

	Correlation Coefficient
GroupA	0.254
GroupB	0.553
GroupC	0.518
GroupD	0.673
GroupE	0.501
GroupF	-0.273

Table 5: Mean of Stay Duration for each user group

	Mean(s)
Isolated User Groups	350400
Non-isolated User Groups	684279

count.

4.2 User Types

Firstly, the analysis focused on isolated users. Isolated users were considered to have shorter stays in the research lab compared to other users. It was hypothesized that there might be a relationship between being an isolated user and the stay duration in the research lab. Therefore, the average stay duration in the research lab for isolated and non-isolated users in May and June 2023 was investigated. The stay duration was measured using beacons distributed to members in the lab, and the time spent in the lab was measured using this beacon system. Users with obviously large values for stay duration, such as leaving the beacon in the lab, were omitted from the analysis. Although differences were observed in the average stay duration for each user group, as shown in Table 5, conducting Welch's t-test for the average stay duration yielded a p-value of 0.160, indicating no significant differences among the user groups.

Next, the social graph created in this work was analyzed to identify users central to organizational communication. Degree centrality[16] and Eigenvector centrality[17] were used as indicators to define central users. Degree centrality evaluates centrality based on the number of edges each node possesses, while eigenvector centrality assesses centrality based on connections to nodes with high degree centrality. The rankings of users' degree centrality and eigenvector centrality were calculated, as shown in the Table 6. From this Table, it was determined that User Z was the central user in the social graph. Degree centrality and eigenvector centrality focus on the number of edges, but as indicators related to central users, it is conceivable that they have a large degree of adjacency level with many users. Therefore, the number of times each user is the most adjacent user to other users was counted, and the rankings based on these counts are shown in the Table 7. From this Table, it was found

[16] `https://networkx.org/documentation/stable/reference/algorithms/generated/networkx.algorithms.centrality.degree_centrality.html#networkx.algorithms.centrality.degree_centrality`

[17] `https://networkx.org/documentation/stable/reference/algorithms/generated/networkx.algorithms.centrality.eigenvector_centrality.html#networkx.algorithms.centrality.eigenvector_centrality`

Table 6: Ranking of Degree Centrality and Vector Centrality

Ranking	Degree Centrality	Vector Centrality
1	UserZ	UserZ
2	UserF	UserF
3	UserG	UserH
4	UserH(Tie)	UserG
5	UserI(Tie)	UserI
...	...	...

Table 7: Aggregate of the number of users with the Highest Adjacency Level for each user

Ranking	Name	Total
1	UserZ	44
2	UserF(Tie)	3
3	UserG(Tie)	3
4	UserJ(Tie)	3
...	...	...

that User Z was the most adjacent user to over half of the 68 users overall. Therefore, the frequency of being the most adjacent user to each user could be related to central users.

Additionally, User Z ranked third overall in contribution level among all users and also third in the number of messages posted. However, there is another user, User K, who ranks higher in both categories, but is not a central user. As a hypothesis, it was considered that being a central user might be influenced not only by the number of messages posted, but also by posting more messages in channels with a larger number of members. To explore this, a value was calculated for each user by adding the weight of the number of members in the channel where each message was posted. The results are shown in the Table 8. The results showed that the value for User Z was the highest. Therefore, it was concluded that posting messages in channels with a larger number of members could be a factor in becoming a central user.

4.3 Regarding the scope of the data used for analysis

The data used in this analysis was limited to public channels within the workspace, so analysis of private channels and direct messages was not possible. Therefore, it is conceivable that users who became isolated in this analysis might be engaging in significant commu-

Table 8: Sum of values with Channel Members' Weight added to each Message

Ranking	Name	Total
1	UserZ	17472
2	UserK	8979
3	UserJ	6208
4	UserL	2679
5	UserH	2649
...	...	...

nication in private channels. In the future, we would like to conduct analysis including private channels in the creation of social graphs, as well as examine differences in contribution level and adjacency level between public and private channels on a per-user basis, along with their contributing factors. However, since handling data from private channels requires caution due to privacy considerations, we would like to explore appropriate handling methods. Additionally, this study evaluated data from only one research lab. Since the results of the analysis for isolated users and inactive groups may vary depending on factors such as the number of individuals and the environment of the organization handling the data, we aim to conduct analysis on data from multiple organizations in the future.

5 Conclusion

In this study, we visualized communication using social graphs and identified isolated users with the aim of intervening in organizational communication and improving overall performance. To this end, we defined user contribution level and adjacency level using Slack messages, reactions, mention messages, and thread information as a novel approach. This enabled us to visualize communication within the organization. Regarding the analysis of the social graph, positive correlations between contribution level and the message-to-contribution ratio were observed in four out of six clustered groups, excluding isolated users. Furthermore, regarding isolated users, no significant differences were observed in comparison to non-isolated users concerning the duration of stay in the research lab, contrary to the hypothesis. For central users, it was found that in the social graph created in this study, there exists a user with the highest degree centrality and vector centrality, indicating that this central user is the most adjacent to other users, and factors such as the number of times being the most adjacent user for each user, and the number of messages in channels with a large number of members could contribute to being a central user.

The visualization of the social graph and the identification of isolated users conducted in this study allow us to pinpoint users who should receive appropriate interventions to address communication deficiencies within the organization. This, in turn, can promote the improvement of work engagement within the organization.

6 Future Work

As a future prospect, since the clustering method currently used only utilizes adjacency level for clustering, we want to develop a clustering method that also considers contribution level to perform clustering that reflects more data. Additionally, based on the analysis results for central users, there is room for adjustments such as changing weights based on the number of channel members to better reflect user centrality in the organization, particularly for messages. Similarly, regarding contribution level and adjacency level, we currently calculate the ratio of weights for messages and reactions as 1:1, but since there are differences in the costs associated with each correspondence, we would like to consider adjusting the weight ratio based on factors such as their respective totals. We are also considering a clustering method that categorizes users into "central users," "isolated users," "intermediary users," and "other users" based on data such as nodes and edges, and we are exploring mechanisms for interventions to increase connections with other users for isolated users and to connect groups of users who are not intimate.

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