Enhancing Distributed Collaboration Using Sociometric Feedback

by

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Abstract

Distributed collaboration is often more challenging than co-located collaboration as many of the social signals become lost in computer-mediated communication. I propose a system that improves the performance of distributed groups using sociometric feedback. Sociometric feedback is a real-time visualization of the quantitative measurement of social interactions. Sociometric feedback helps distributed group members have a better understanding of the members that are not co-present. Moreover, a persuasively-designed sociometric feedback can control the direction of change in the communication pattern of groups, so that the change can lead to a performance increase.

Laboratory studies verify the strong relationship between communication patterns and group performance in two types of tasks. Based on these relationships, sociometric feedback is introduced to enhance both the communication pattern and the performance of distributed groups. Results show that sociometric feedback influences the communication patterns of distributed groups to be more like that of co-located groups, which results in an increase in performance. Additionally, sociometric feedback helps groups to have a more consistent pattern of communication even when they face a change in member distribution; this effect also results in an increase in performance. Data from two pilot studies of real-world teams suggests that sociometric feedback may be applicable to real-world organizations to benefit their performance.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

Recall the last time you were assigned to a new group. You met your group members for the first time, introduced yourself, and then your group started to talk about the tasks and the roles of your group. But as the conversation developed, the content of the conversation was not the only thing that you were focusing on: your senses were intensely observing the signals that lay underneath the spoken language. Information, such as who was sitting next to whom, who talked the most, who sounded the most confident, who asked questions, and who replied, gave you a sense of how the group works and how you should behave in the group. Now imagine that this first encounter with the group was through a conference call. Your ears and brain had to work even harder to get a sense of the other group members: were they paying attention, were they expecting you to say something, or did you say something stupid? You put in extra effort but it was much harder for you to get a clear understanding of what was happening and how the group worked. You noticed that your behavior was somewhat different from what you normally do when you are in the same room with people: you talked more (or less) than usual; you didn't know when you were supposed to speak; and sometimes you were less confident about what you have said since you couldn't see the responses of other people.

As you can recall from your personal experience, distributed collaborations are quite different from co-located collaborations. Researchers in organizational behavior have also confirmed the difference. Hinds and Bailey [35] have demonstrated that distributed collaborations have very different dynamics compared to co-located collaborations, and that these differences often lead to poorer performance. Rocco [70] and Bicchieri and Lev-on [11] found that trust between group members breaks down in computer-mediated communications (CMC). Bouas and Arrow [14] found that group identity levels in distributed groups were much lower compared to co-located groups.

Then why do distributed collaborations differ so much from co-located collaborations? The content is surely not the missing piece, as communicators have no problem sending and receiving content using voice or text. Then what missing piece makes distributed collaborations so much harder than co-located collaborations? I believe one of the main factors is that social signals are lost in communication. Social signal are subtle patterns of behavior in how one interacts with other people [66]. The exchange of these social signal often provide context to the interactions. For example, someone looking away or rocking their body back and forth may reveal that they are bored. Someone staring at you during a pause of conversation may be signaling that they want to hear your thoughts. These signals often function as a feedback to one's communication style, resulting in members adjusting their behavior.

In distributed groups, the functionality of social signals is hindered, making it difficult for groups to coordinate their communication [35, 62]. The lack of social signals makes it harder for group members to understand the current state of the group communication, and how individuals should behave accordingly. Additionally, the lack of feedback from one another makes it difficult for group members to reflect on their own behavior. The common use of question marks, exclamation marks, capital letters, and smiley faces demonstrates the tendency of people trying to augment social signals in text-based communication. Communication technology enables some level of exchange in social signals. State-of-the-art video conferencing systems allow the exchange of richer visual signals. However, differences still exist making people want to meet face-to-face. Sense of proximity, back channel conversations, and eye contact are examples of social signals that are still not communicated in today's computer-mediated communication (CMC).

With the advance of sensing technology, we can use electronic sensors to measure many of these social signals, which are embedded in the communication patterns of groups. Many researchers have shown that we can obtain a quantitative understanding of group collaborations by measuring communication patterns of groups [4, 18, 21]. By comparing quantified communication patterns to quantitative performance measures, I aim to reveal the quantitative relationship between group communication pattern and group performance. For example, we may find that the amount of talking has a positive correlation with how many ideas a group generates in a brainstorming session. Understanding the relationship of communication patterns and performance would help us identify communication patterns that lead to higher performance, which can be valuable information used to help teams improve their performance.

Not only has the advance of technology allowed sensing of social signals, the advance of network technology enabled us to quickly transfer the measured data between geographically distributed locations. By transferring communication pattern data measured between distributed teams, we may be able to bring back the functionalities of the lost social signals. For example, members in distributed teams may have a more difficult time balancing their participation as they get little feedback on their behavior through social signals. However, we may be able to overcome this problem by measuring the participation balance of the whole group and informing that data to all the distributed members. Hence, I propose (i) to aggregate communication patterns measured from distributed groups in order to gain an understanding of how the whole group is interacting and (ii) to use the aggregate data to provide feedback as a method to help groups adjust their communication patterns. I define this sensor-based feedback of social signals as "sociometric feedback".

Once the social interaction data is captured, there are many ways to present the information. I chose to use visualization as the main mode of output as often this mode is not fully utilized in distributed collaboration. When visualizing the data, I apply ambient interface methodologies to visualize the social signals in an effort to not distract the users from their main task [37]. Additionally, methods from persuasive technology are introduced in the design so that the visualization can have control over the direction of change that it causes

[28].

I hypothesize that sociometric feedback helps distributed groups to adjust their communication, making their behavior and performance approach that of co-located groups. These hypotheses are based on Walther's finding [81] in which he found that a well-designed computer medium can support rich interpersonal communication, allowing distributed groups to behave more similar to co-located groups. I believe that by measuring and communicating social signals in CMC, we can enhance the richness of interpersonal communication of distributed groups to a level similar to that of co-located groups.

Therefore, the research questions can be summarized as:

> RQ1. How can we measure communication patterns of collaborating groups and how can it be provided as real-time feedback?
>
> RQ2. What is the relationship between group communication patterns and group performance?
>
> RQ3. What is the effect of sociometric feedback on group communication patterns and performance?

And as a related question to RQ3, I also ask:

> RQ4. What is the effect of sociometric feedback on group communication patterns and performance when groups face change in member distribution?

I address each of these research questions, in the following chapters.

1.1 Research Framework

To answer the aforementioned research questions, I take an empirical approach. The research framework that I use can be found in Figure 1-1. First, I use electronic sensors to

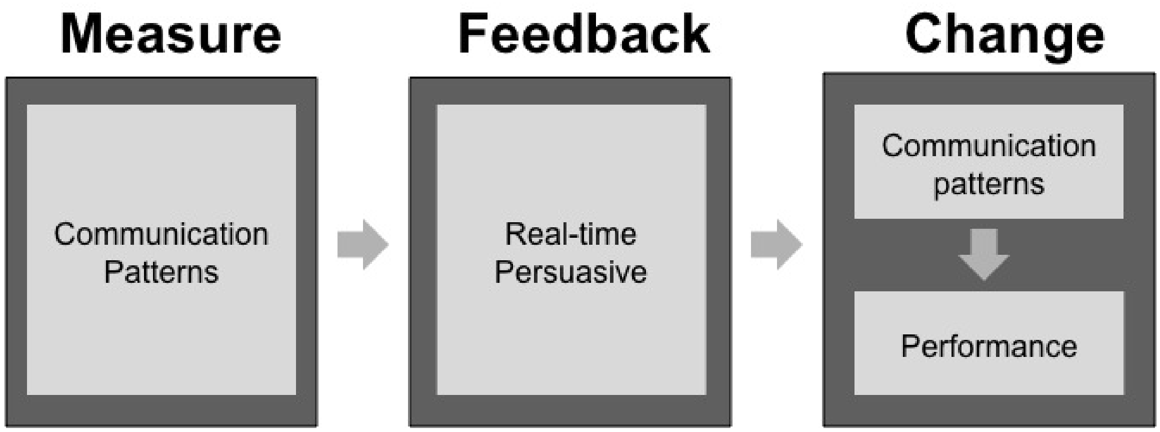


Figure 1-1: The research framework

measure the communication patterns of groups. This measurement, combined with quantitative measurement of performance, will provide an understanding on what type of communication patterns lead to higher performance. Second, the measured communication pattern is visualized as feedback in real time. I chose to do this in a persuasive manner, so that the sociometric feedback can control the direction of change. Finally, I aim to observe the change occurred by the real-time feedback. I hypothesize that the communication pattern and the performance of a group is tightly coupled, such that once a group's communication pattern is changed, a change in performance will follow.

The following chapters follow each step of the research framework. In chapter 2, I introduce the technology to measure communication patterns and to visualize the feedback in real-time. Then in chapter 3, I verify the relationship between group communication patterns and group performance. Based on this relationship, I verify the effect of the sociometric feedback on communication patterns and performance in chapter 4. Chapter 5 explores the same research question in groups in which the member distribution is changing. I close the dissertation by showing possibilities of generalization to real-world teams.

1.2 Related Work

1.2.1 Communication Patterns and Group Performance

The communication patterns of groups have a strong relationship with the performance of groups. Bavelas argued that task-oriented groups tend to adjust their communication patterns so that the patterns will permit the easiest and most satisfying flow of ideas [8]. Hence, the degree of how well the group made the adjustment is strongly correlated with outcome of the task. Leavitt experimentally tested this relationship between group communication patterns and their performance [53]. He found that the communication patterns within which the groups worked affected their behavior, such as accuracy, total activity, satisfaction of group members, emergence of a leader, and organization of the group. Out of the various communication patterns that Leavitt observed, the centrality of communication patterns was the factor most clearly correlated with the group performance.

In addition to arguing that there is a strong relationship between communication patterns and performance, Bavelas and Leavitt also emphasize that this relationship is dependent on the type of task that the group is involved in. They state that, since the communication pattern is shaped in response to the task provided, the optimum communication pattern for a task heavily depends on the specification of the task. Hence, the relationship between communication pattern and performance will vary in characteristics for different tasks, and the degree that they are correlated will vary as well. For example, the number of turn transitions may correlate to the performance of a brainstorming task, whereas the balance of participation may correlate to the performance of an information-sharing task. However, for a quiz-solving task, in which prior knowledge of members drives the ability to answer the question, the communication pattern of groups may not have a strong impact on group performance. Bavelas and Leavitt's argument is in line with the media richness theory developed by Daft and Lengel [22]. The media richness theory suggests that the specification of the task defines the requirement of how rich the media of communication should be. Therefore, the level of social cues and the pattern of communication required for a successful outcome differs depending on the task.

Based on these findings, we can posit that there exists a relationship between communication patterns and performance for collaborative tasks. However, this relationship will differ in characteristics and degree depending on the task.

1.2.2 Distributed Collaboration

Many researchers have compared computer-mediated distributed collaborations and co-located collaborations. Most have consistently found that the communication patterns of distributed collaborations significantly differ from that of co-located collaborations. Cohen found that there were almost twice as many speaker switches in a face-to-face meeting than in a Picturephone meeting [19]. Sellen found through her experiments that there was significantly more overlap in face-to-face collaboration than in collaborations using video conferencing [72] and O'Malley and colleagues discovered that distributed groups had more longer and more interrupted dialogs [63]. Kleji et al. confirmed earlier findings by showing that, compared to face-to-face groups, video-teleconferencing groups took fewer turns, required more time for turns, and interrupted each other less [79].

Along with the differences in the communication patterns, differences were observed in the work processes of groups. Jonassen and Kwon showed that when group problem solving is computer mediated, communications become more task oriented with clearer role expectations, while face-to-face communications are more cohesive and personal [38]. A cluster analysis of communication patterns showed that computer-mediated group decisions more closely resemble the general problem-solving process of problem definition, orientation, and solution development as group interaction progress, while the face-to-face group interactions tend to follow a linear sequence of interactions.

The differences in communication patterns and work processes also led to a difference in performance: distributed groups tend to have lower performance than co-located groups. Bos et al. explored how different modes of communication affect group cooperation level [13]. They discovered that text-based communication showed the lowest level of cooperation, followed by audio and video. Face-to-face communication displayed the highest level of cooperation. They found that in distributed collaborations mediated by computers, the limited modality of communication delays the development of trust and makes it vulnerable. Olson and Olson found that distributed teams tend to have lower performance since they face difficulty in sharing common ground, coupling of work, collaboration readiness, and collaboration technology readiness [62].

Prior work shows that distributed collaborations are different from co-located collaborations in its pattern of communication, work processes, and performance. The difference is often in a direction unfavorable to distributed collaborations. Therefore, we aim to improve distributed collaborations so that it can have performance on a par with that of co-located collaborations.

1.2.3 Feedback

Feedback has been used as a mechanism to improve group performance for a long time. Through a study on surveys, Ammons found that feedback, in the form of knowledge about one's performance, affects an individual's behavior [3]. Bakera showed that feedback on performance, along with goal setting, had a positive influence on group performance helping groups to do a better job in achieving their goals [9]. Pritchard et al. used similar approaches and found that group-level feedback increased productivity to an average of 50% over the baseline control condition [68]. Feedback on performance has been shown to affect numerous organizationally-relevant outcomes such as employees' job motivation, satisfaction, absenteeism and turnover [2]. Kluger and DeNisi's feedback intervention theory assumes that behavior is regulated by comparisons to standards or goals and that feedback interventions affect behavior by changing individuals' locus of attention [47]. Hence, the knowledge of a group's performance can have a positive impact on their future performance.

Feedback in the form of social signals has also been shown to have an impact on group performance. Kraut et al. found that in a information-sharing task, the verbal responses of the listeners functioned as a form of real-time feedback [50]. The feedback provided by the listener, either through short "um"'s and "uh-huh"'s or by actively asking questions, facilitated information flow and common ground sharing, enhancing the outcome of the task. Leavitt and Mueller found that more feedback on the communication resulted in increasing accuracy in task, and the significance of the effect was equally present in multiple tasks [54].

Therefore, the expression of social signals can function as a feedback, influencing the communication pattern and improving the group performance. However, this functionality is obstructed in distributed collaboration, hence I propose utilizing sociometric feedback to reconstruct this functionality in distributed groups.

Chapter 2

Technology to Measure Group Communication Patterns and Provide Feedback

Communication is an essential component of successful group collaboration. A group needs to properly communicate in order to define their goals, designate tasks, and cooperate to accomplish their goals. Therefore, understanding the communication among group members can give us insight into the processes of group work [49]. Moreover, real-time measurement allows us to provide feedback to groups during their communication in order to have an impact on their communication style and performance. This chapter introduces the technology and methodology that enable automatic measurement of individual and collective patterns of behavior, identify communication, and enhance social interactions by providing feedback to groups.

Traditional methods to measure and evaluate human behavior, such as surveys, often suffer from subjectivity and memory effects. Human observers allow real-time observation, but they can be subjective and have the burden of high cost. In [65], Pentland envisioned a device that could accurately and continuously track the behavior of hundreds of humans at the same time, recording even the finest scale behaviors with great accuracy. Such a device would replace expensive and unreliable human observations with automated, computer-mediated ones. The automatic discovery and characterization of face-to-face communication would allow us to objectively gather interaction data from large groups of people. This approach could potentially remove two of the current limitations in the analysis of human behavior: the number of people that can be surveyed, and the frequency with which they can be surveyed.

There are various methods to provide feedback on group communication patterns. The most traditional method is a post-task evaluation, in which the group members reflect on their communication patterns or have external observers provide input on areas of improvement. Due to its post-hoc nature, this method inherently cannot be helpful at the time of the task. Moreover, this method requires much time, effort, and expertise from the members or the human observers. Real-time intervention has been practiced in the form of a human meeting facilitators. A facilitator is someone who enables groups and organizations to work more effectively; to collaborate and achieve synergy [39]. The facilitator encourages full participation, promotes mutual understanding and cultivates shared responsibility. By supporting everyone to do their best thinking, a facilitator enables group members to search for inclusive solutions and build sustainable agreements. Our goal is to use automatic sensing technology to replicate this role of a facilitator, with drastically lower cost. Minimizing obtrusiveness is a critical factor to take into consideration when designing facilitating systems: interventions must not distract the group members, it must not take the group's attention away from the main task.

2.1 Related Work

2.1.1 Technology to measure group communication

Many scholars have researched methods to measure group communication patterns. Scholars as Dong et al., DiMicco et al., and Curhan and Pentland used microphones to use audio input as means to understand group communication patterns [21, 24, 27]. Using microphones, Dong et al. mapped the styles of speech to the functional roles that people take in

(a) Audio (b) Video (c) IR

Figure 2-1: Examples of prior technology capturing group communication patterns.

solving mission-oriented tasks. Curhan and Pentland found that the speech patterns of the first 5 minutes of a negotiation session predicted the final outcome. Dimicco et al. created a custom microphone box that collects and synchronizes audio input from four different microphones (Figure 2-1a).

Along with audio, video analysis can add more information in understanding group dynamics. Aran and Gatica-perez, Brdiczka et al., and Pianesi et al. fused video cues with audio cues to better understand the group behavior [4, 16, 67]. Using video, they analyzed visual cues to calculate the amount of movement and facial features to understand the expressed social signals (Figure 2-1b).

There have been efforts to use other modalities to understand group dynamics. Choudhury et al. invented the Sociometer (Figure 2-1c) which had IR transceivers to detect who the wearer is facing. Sung and Pentland used accelerometers on arms patches to detect stress and bluffs of poker players [76]. Gips proposed the Social Motion application, which fused two types of sensors (proximity sensors and motion sensors) to infer the underlying social structure of groups [30].

2.1.2 Feedback on group communication patterns

To change the communication patterns of groups, we propose using automatic measurement and real-time feedback. There are many examples of communication patterns being changed using real-time feedback. The most common example is encouraging balanced participation by showing the speaking ratio of the group members [10, 24, 52]. A fun example of Basu et al. is the use of an actuator to increase the intensity of lighting on under-participating individuals to emphasize their presence [7]. There have been few efforts to apply these technologies to distributed collaboration. One example is work by Leshed et al. where they show language-based feedback on a chatting system using a peripheral visualization [56]. Feedback on proportion of agreement words and overall word count was presented. This system made participants express more agreements and focus more on their language use.

2.1.3 Persuasive Technology and Peripheral Interfaces

Fogg defined persuasive technology as an interactive technology that changes a person's attitude or behaviors [28]. He has shown multiple examples of how technology can change one's behavior using its presence and the ability to understand users. Kumar and Kim applied the concept and provided feedback to drivers on how much they are speeding over the speed limit [51]. The feedback was designed with the intention to make drivers speed less, and the effectiveness of the feedback was validated through a laboratory study. The effect was found even in the drivers who did not understand the intent of the visualization.

When designing these persuasive interfaces, one needs to consider the cultural background of the target user. Takeuchi and colleagues found that people implicitly apply social norms in human-computer interaction based on their own cultural background [77]. Hence, to encourage a norm to users, one needs to design the interface according to the intended user's cultural background. However, one can make use of more universally common trends. For example, the affective meaning of color is shown to be quite universal [1]. While focusing on western users as target users of the persuasive interface, I tried to utilize concepts that are presumably universal to other cultures, i.e. colors, balance in location, and balance in size.

One important point in persuasive technology is that the technology should not distract users from their main task. This is in line with concept of peripheral interfaces was raised

Figure 2-2: The Meeting Mediator System

by Weiser and Brown, with the intent of providing information to the users with minimal distraction [82]. Weiser and Brown showed an example of such interface by displaying the network traffic by relating it to a live wire movement. They provided this information to change the network usage behaviors of users, with minimal distractions. Ishii and Ulmer expands on this concept building many ambient interface prototypes that provides information to the user, using only the periphery of their attention [37]. I applied the methodologies from persuasive technology and peripheral interfaces to create a prototype that changes the behavior of groups without distracting them from their main tasks.

2.2 Meeting Mediator

I introduce a system called Meeting Mediator (MM, Figure 2-2), which is an example of a sociometric feedback system. The system consists of (i) wearable badges that measure communication patterns of groups, (ii) a back end system that synchronizes and analyzes the data, and (iii) a mobile phone display that provides real-time feedback based on the measurements. Examples of the system being used is shown in both a co-located group (Figure 2-3) and a distributed group (Figure 2-4).

Figure 2-3: The Meeting Mediator System used in a co-located group

Figure 2-4: The Meeting Mediator System used in a distributed group

2.2.1 Sociometric Badges

The Sociometric badge (Figure 2-2, right) is a wearable electronic sensing device that collects and analyzes social behavioral data [61]. It is designed to be worn around one's neck like a typical company ID badge. Its current capabilities include:

- Extracting speech features in real-time to measure nonlinguistic social signals. The badge does not record any speech content, but is capable of identifying social behavior such as speaking time, speaking speed, and speech energy of the user. Turn taking or short affirming phrases reveal social dynamics that can be measured through synchronization of badges of multiple participants.

- Measuring body movement using a single 3-axis accelerometer. This can detect individual activities such as gestures and posture as well as social interactions such as body movement mimicry or rhythmic patterns.

- Real-time sending and receiving of information over 2.4GHz radio to and from different users and base stations for real-time communication.

- Detecting proximity data using the 2.4 GHz radio to understand the relational distance and position of multiple wearers. The badge can detect other badges within a 10m radius in an one-meter resolution. This function can be used to detect the distribution of group members.

- Capturing and identifying face-to-face interaction using an IR sensor. By detecting the face-to-face alignment of individuals we are able to detect encounters as well as postural direction.

- Performing indoor user localization by measuring received signal strength from fixed based stations.

Figure 2-5 shows sample data. This is data collected while a couple was shopping for furniture [45]. A couple was asked to wear the sociometric badges during their time of strolling

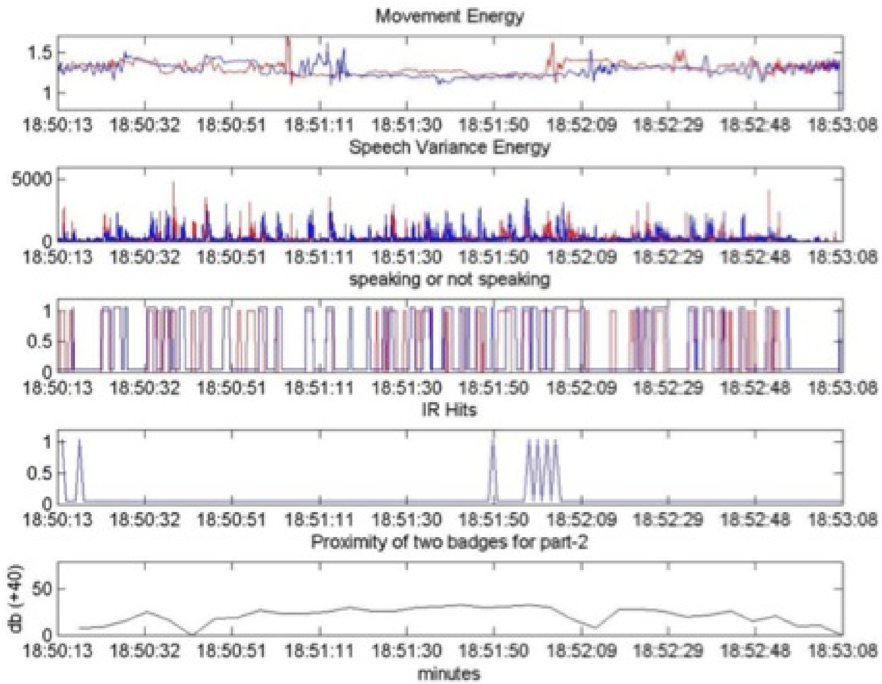


Figure 2-5: Sample badge data of a couple shopping for furniture

through a furniture store and browsing multiple items. This data shows the multimodal data collected while looking at a single item, a couch. The red lines indicate the female's data and the blue indicates the male's data. The X-axis indicate timeline. The top row shows how the couple moved about during the period: the flat area in the middle corresponds to the time when the couple was sitting down on a couch. The second row shows the speech energy of the couple: you can see how loud they were and how much variance in speech there was. The third row shows the logical value of whether each individual was speaking. One can see the turn transitions of the couple as well as the overlap in speech. There is a lot of overlap in speech especially during the time when they were sitting on the couch. The fourth row shows IR hits which occurs when the couple turned their body so that they were directly facing each other. The last row shows the signal strength of the radio which estimates the proximity of the couple. The multimodal data provides a broad understanding of the dynamics and communication that happened between the couple.

Measures

The sociometric badge can detect a wide range of communication features. Out of all the features, I chose to observe nine different features in the laboratory studies using the sociometric badges. Though many of our measures are individual based, I only used group level measures in the analysis as individual data points, because members' actions within a group is highly dependent on each other.

- *Movement energy* is the average amount of body movement, i.e. the amount of gesturing and moving during conversation. The average of the individual values is the group measure.
- *Movement energy variance* is the variation in movement energy over time which indicates the abruptness of movements. The average of the individual values is the group measure.
- An individual's speaking time is the fraction of time during which an individual speaks, regardless of interruptions or overlapping speech from others. The group's *speaking time* is the average speaking time of all four members.
- The *balance of speaking time* is the standard deviation of the speaking time between members. Hence, higher values correspond to more varied speaking time among the members. This is measure directly addressed by the Meeting Mediator's visualization.
- *Overlap speaking time* of a group is the fraction of time that more than one individual was talking.
- *Speech energy* is the variation in volume. High speech energy tends to make people sound more expressive [66]. We use the average of the individual values as the group measure.
- *Speaking speed* is measured by approximating the number of voiced segments per speaking time [18]. When people speak, voiced and unvoiced segments are alternated.

Faster speech results in more number of voiced segments per second. The average of the individual values is used as the group measure.

- A speech segment is any one continuous stream of speech from an individual, regardless of interruption or overlap from other participants. A segment ends either by an interruption caused by another participant that resulted in the speaker to stop speaking or a significant length of silence. So the *average speech segment length* is the average length of uninterrupted speech segments. The average of the individual values is the group measure.

- The exact number of turns each person is measured and summed up to measure number of turns. *Number of turns/sec* is the normalized value over the duration of the discussion. This frequency of turn-transition will be used interchangeably with *the interactivity level* of the group as the two have a very strong positive relationship [59].

2.2.2 Data Upload and Synchronization

Once the sociometric badges collect data, the mobile badges can wirelessly transfer their data to a local base-station badge, which is tethered to a laptop computer. Each mobile badge transmits its data every 5 seconds. Whenever the laptop computer receives data from any of the mobile badges, it transfers the data to a central server where the database is located. The server accesses the data from all four badges and performs synchronization and analysis to calculate features such as speaking balance, turn taking, and speaking speed. When groups are distributed, each room needs a set of a base-station badge and a laptop computer to upload the data to the central server. All other procedures are identical to the co-located condition.

2.2.3 Visualization on Mobile Phones

The information collected by the sociometric badges can be visualized on computer displays in real-time. The visualization is designed to promote change in individual and group

Group-level feedback	Individual-level feedback	
Group Norm	Individual norm	Group norm
Balanced participation	Moderate % of speaking time	Balanced participation
High overall interactivity	High individual interactivity	Equally high interactivity
–	Balanced turn transitions with all other members	Evenness in turn transition (low centrality)

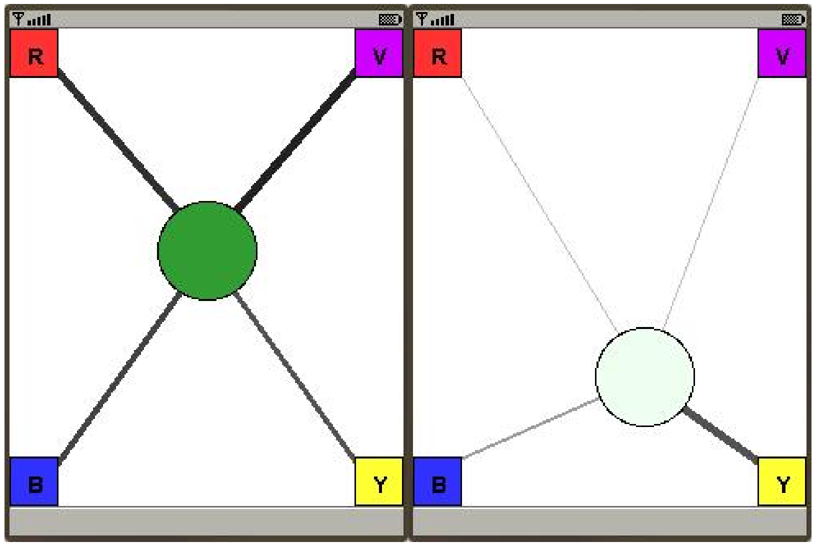
Table 2.1: Norms encouraged by the two types of feedback.

behavior. The design of the feedback is obviously dependent on the goal of the task. For some tasks, such as brainstorming, more interaction and balanced participation may increase performance, whereas in other tasks, such as a unidirectional information sharing, it may be preferred that groups have an imbalanced speaking time. Therefore, for different tasks, the visualization of the same data should be designed accordingly in order to encourage a different direction of change.

Two examples of feedback are designed for four-person groups: group-level feedback and individual-level feedback. Both of these prototypes were designed for tasks for which balanced participation and higher interactivity is generally beneficial. By no means does this feedback apply to all types of tasks. But as a proof of concept, we chose these two examples of visualization to show that real-time sociometric feedback can indeed change group behavior which results in performance enhancement. The group-level feedback reveals the behavior of all group members so that all members can see their own behavior and the aggregate behavior of other members in the group. The individual-level feedback is a customized feedback to oneself, displaying feedback of the individual behavior in relation to other group members, but does not provide aggregate information about the other members.

Group-Level Feedback

As mentioned earlier, the goal of the group-level feedback is to promote balanced participation and high level of interactivity in a four person group (Table 2.1, column1). Each of the four participants is represented by a colored square in the corner of the screen (Figure 2-6). The color of the central circle gradually shifts between white and green to indicate



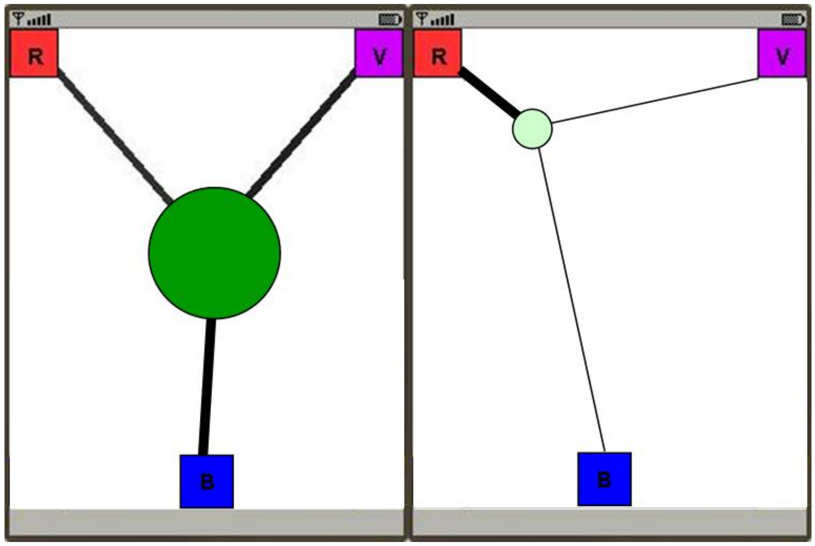
(a) Balanced and interactive (b) Unbalanced and non-interactive

Figure 2-6: Group-level feedback visualization for a four person group. An example of a visualization of a group when (a) every one's participation is balanced with high interaction and (b) one person is dominating the conversation with low group interactivity.

the *overall group's interactivity* (turns/sec), with green corresponding to a higher level of interactivity. *Balance in participation* is displayed through the location of the circle: more a participant talks, the stronger they pull the circle closer to their corner. So the circle is in the center when a group's participation is balanced. In addition, *each member's speaking time* is displayed through the thickness of the line connecting the central circle with each member's corner. The circle moves and changes color gradually as the group is engaged in the conversation. The display is intended to be in the periphery of the user's attention, and updates gradually so that it does not require constant attention from the user. Text and small details were also purposely avoided so that a mere glimpse would be sufficient for information retrieval. Only an extreme change in the group dynamics will draw the user's immediate attention.

Individual-Level Feedback

The individual-level feedback was designed to be customized to each participant. This prototype was designed to promote an individual norm to each of the members, specifically



(a) Balanced and interactive (b) Unbalanced and non-interactive

Figure 2-7: Individual-level feedback visualization for a four person group. An example of a visualization of a group when (a) the person represented by the circle has balanced turn-taking with all other members with high interactivity. (b) the person represented by the circle did not speak much with low interactivity and mostly interacted with the person in Red

to have a moderate percentage of speaking time, high individual interactivity, and balanced turn transitions with all other members (Table 2.1, column 2). Encouraging this individual norm to each of the participants will result in the group behaving in a certain way. If all members speak a moderate amount, the participation will be balanced; if all members are encouraged to have high interactivity, then all the members will tend to have equally high level of interactivity; and if each member has balanced turn taking with all of the other members, the group will have high evenness in turn transitions, i.e. a low centrality in the turn-taking adjacency matrix. Hence, the group norms encouraged by this individual-level feedback are balanced participation, equally high interactivity among all members, and an evenness in turn transition (Table 2.1, column 3).

Each of the other three participants is represented by a colored square in the screen (Figure 2-7). The central circle denotes the individual this feedback is being shown to. The size of the circle shows the *amount of participation of the individual* as a ratio of the total speaking time of the group. This design doesn't neccesarily encourage more or less conversation, but there would be negative connotation only when the circle is too small to see or too big that it covers most of the screen. The color of the circle gradually shifts between white and green indicating the *individual's interactivity level*, with green corresponding to a higher level of interactivity. *Balance in turn transitions* is displayed through the location of the circle: the more turn-taking the individual has with another participant, the stronger the ties will be pulling the circle closer to the other participant. Hence, cliques within a group will be discouraged. The *absolute amount of turn transitions with each member* is shown through the thickness of the line connecting the central circle with each member.

Compared to the group-level feedback, there are two major differences in the design. First, instead of showing the aggregate data, individual-level feedback is showing individual measure of the interactivity level. In the group-level feedback, a group can have a high interactivity level even if one or more individuals have low frequency of turn-transitions, as the overall group aggregate can be high driven by other members. Hence, there could be free-riders. However the individual-level feedback makes sure to encourage all members to be highly interactive by showing their individual frequency of turn transitions. This may encourage all members to have higher interactivity level, decreasing the variance among members. The second main difference from the group-level feedback is that the individual-level feedback displays the turn transition patterns with other members. In the group-level feedback, the position of the circle was defined by the speaking time balance of members. In the individual-level feedback, the circle position shows the balance of number of turns that an individual had with other members, an information not available in the group-level feedback. This information encourages each group member to have equal turn transitions with all other members, prohibiting the turns being centered to any one participant. Hence individual-level feedback will decrease the centrality of turn transitions in groups. Therefore, the norms encouraged by the individual-level feedback include all of the norms encouraged by the group-level feedback and in addition encourages equalness of interactivity and evenness in turn transitions.

2.3 Conclusion

I have introduced the Sociometric Badge, a wearable electronic sensor that detects various communication patterns of groups in real-time. This data can be processed and analyzed in real-time allowing visualization on individual displays. Real-time feedback on a group's communication pattern can have an impact on the group's behavior which may lead to a changed outcome of the group. I utilize persuasive interface design methodologies to encourage change in an intended direction, expecting increase in performance. I give two examples of persuasive sociometric feedback: the group-level feedback encourages balanced participation and high overall interactivity, while the individual-level feedback encourages equal level of interactivity and evenness in turn transitions, along with the norms encouraged by the group-level feedback. Following chapters verify the effect of this sociometric feedback system.

Chapter 3

Communication Patterns and Performance

The main objective of the Meeting Mediator system is to improve the performance of groups by changing their communication patterns. However, for the system to be effective, we first need to confirm (i) the relationship between communication patterns and performance and (ii) identify which communication pattern corresponds to higher performance. Once these two factors are confirmed, then we can examine the effectiveness of our system, this examination is done in chapter 4. To test the relationship between communication patterns and performance, we used two group tasks in laboratory settings: a cooperation task and an information-sharing task. These two tasks were selected as they cover real-world team practices and are collaborative tasks, in which we expect to find a strong relationship between communication patterns and performance. The goal of the study is to verify which pattern of communication increases the performance in the two tasks. The studies were conducted in collaboration with Prof. Alex (Sandy) Pentland.

We expect that the patterns of behavior that leads to high performance will differ significantly between the two tasks as Hackman and Vidmar found that the type of task strongly affected the performance characteristics [32]. Hence, we believe that a pattern of behavior that is beneficial for the performance of the cooperation task, may not necessarily be beneficial for the information-sharing task, and vice versa.

3.1 Cooperation Task

To test the cooperation level of the groups, we use a social dilemma task. Social dilemma task is a mixed-motive task often used in social psychology to measure the level of cooperation. A social dilemma can be defined as a situation in which a group of people must decide between maximizing selfish interests or maximizing collective interests [48]. It is generally more profitable for the individual to maximize selfish interests, but if all do so, all are worse off than if everyone had maximized collective interests. The performance of the group is measured as the sum of earnings of all members. The paradigm has often been deployed in the field of HCI, where it has been used as a common measure of cooperation in groups [15, 44].

3.1.1 Related Work

In numerous experiments of social dilemma, researchers found that cooperation is not a natural choice when immediate selfish interest is in conflict with the group's interest. This is especially true for geographically distributed groups. Researchers such as Rocco [70] and Bicchieri and Lev-on [11] found that trust breaks down in computer-mediated communications undermining cooperative behavior. They found that it is extremely difficult for distributed groups to establish and maintain trust and cooperation compared to groups communicating face-to-face. Bos et al. further explored how different modes of communication affect trust and cooperation [13]. They discovered that groups communication via text showed the lowest level of cooperation, followed by audio and video. Audio and Video were similar in their level of cooperation, whereas face-to-face communication displayed the highest level of cooperation. The cooperation level of groups that communicated via audio and video slowly and vulnerably increases as they repeated the studies over a long period of time. However text-only communication never reached the level of face-to-face communication during 30+ trials.

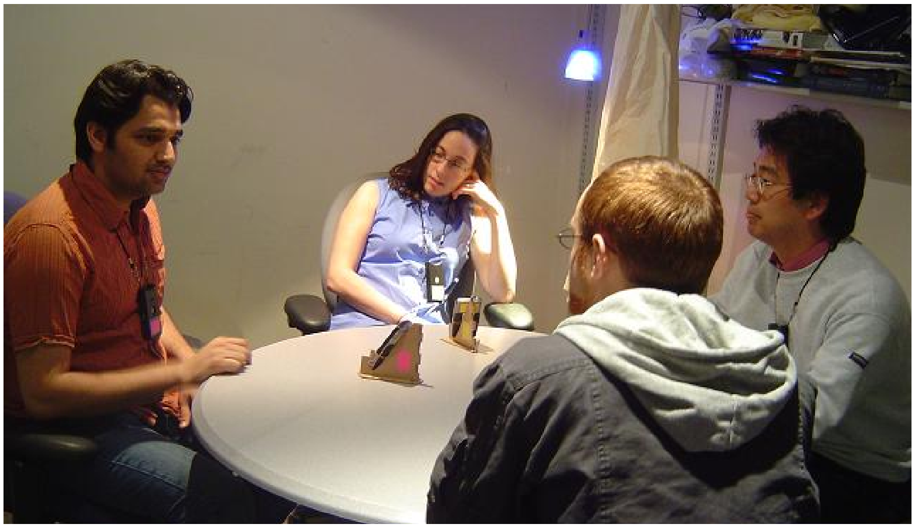


Figure 3-1: The co-located setup: subjects wear the sociometric badges around their neck. The badges communicate with each other to aggregate the communication patterns of the whole group. The processed data can be visualized on personal displays facing each subject.

Hence, we see that in CMC, the limited modality of communication delays the development of trust and makes it vulnerable. Out of the variety of communication methods, we chose to use only audio as our medium of communication for distributed groups. Our decision was because audio is still the most common medium of synchronous communication when people are distributed. Moreover, audio seems to be a good representative of the current state of distributed communication, as it has similar temporal patterns of trust development with video conferencing.

3.1.2 Methods

Experimental Setup

We conducted a laboratory study to examine the relationship between the communication patterns and the group performance of the cooperation task. We recruited 4 participants for each session who were asked to wear a sociometric badge throughout the whole duration of the experiment. As the main goal of the experiment was to verify the effect of sociometric feedback, a control setting with no feedback was compared to an experimental setting where

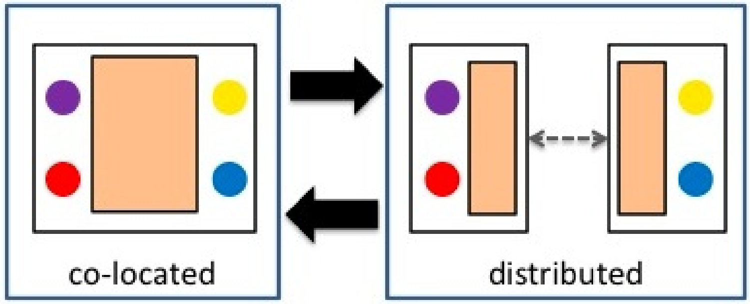


Figure 3-2: Each group performed two rounds of the social dilemma task, once co-located and once distributed into pairs

there were four mobile phones sitting in front of the table, facing each participant (Figure 3-1). However in this chapter, we combined the data from the two conditions to find the general relationship between communication patterns and group cooperation level regardless of the condition.

Each group participated in two rounds: once with all group members co-located in one room and once separated into pairs in two different rooms (Figure 3-2). The sequence was counter-balanced. When distributed, the participants were not able to see the participants in the other room and were only allowed voice communication. Again, to find the general relationship between communication patterns and group cooperation level, we took the average value the two rounds for both communication patterns and performance when comparing the two.

Participants

We recruited 34 groups of four subjects each, a total of 136 participants. Subjects were recruited on multiple university campuses and through public Internet message boards. Every effort was made to keep subjects from having prior knowledge of one another. All subjects were offered a flat fee of $9 for their time and an additional payment between $6-$34, depending on the results of the social dilemma game. Sociometric badges were provided to all subjects to measure group communication patterns. The total number of groups included in the analysis is shown in Table 3.1.

	# of groups w/o Feedback	# of groups w/ Feedback
Co-located first	8	9
Distributed first	8	9

Table 3.1: Number of four person groups included in the analysis of the cooperation task.

Tasks and procedures

To provide a social dilemma situation, we created a conflict between maximizing collective interests and selfish interests: all subjects were told that the goal of the task was to maximize group earning, but the payoff structure was dependent on personal performance. Each subject was given sixteen $1 bills, of which they could invest any partial amount to the group fund and keep the rest for themselves. The total money gathered in the group fund was increased 50% by the experimenters and divided equally among the four participants regardless of how much each subject invested. Hence, investing all $16 to the group fund would help increase collective interests, but keeping all $16 would maximize personal earnings given a set of decisions of the other participants. However, if all participants were to keep all their money, all participants would earn 50% less than what they would have earned if everyone invested all. The instruction sheet had a sample calculation table and the experimenter confirmed that all subjects comprehended the situation and the consequences of their decisions.

Once all participants understood the problem and the goal of the task, each group was given up to 10 minutes to discuss their group strategy. Badge data collected during these discussions were analyzed as we hypothesized that the communication patterns of these discussions would predict the individual private decisions made by the participants after the discussion has ended. After the discussion time, participants were asked to turn away from each other to make their contribution decisions into two envelopes (one labeled *group* and the other labeled *keep*) and then handed both envelopes to the experimenter so that individual decisions were not known to the other participants. Once all the envelopes were collected, the experimenter announced the total amount in the group fund and the amount to be distributed. The individual contribution amounts were never revealed.

The same procedure was repeated twice: once co-located and once distributed with the sequence counter-balanced. After the first round two of the subjects were asked to move. In both co-located and distributed settings, the earnings were dependent on the decisions of all four participants, requiring all participants to collaborate to maximize their group or individual earnings. All subjects received the average of their earnings in the two rounds. After each round, the total amount in the group fund was announced to all participants. Hence in the second round, the subjects knew the total group fund amount of the first round. Subjects filled out a pre-task survey and two post-task surveys, one after each round.

Performance Measures

Level of *cooperation* is measured by the amount contributed to the group fund. Each individual had two chances to invest $0 to $16 to the group fund. Average of the two values is used as the individual measure of cooperation. The group measure is the sum of the four individual values, which the ranges from $0 to $64.

Another measure of performance is the level of *defection*. Defection is the difference in the amount that a member promised and the amount that they actually invested. Before making individual decisions, groups were given the opportunity to discuss their strategy. At this time, most group members verbally expressed how much they will put in the group fund. For most groups, this amount was the same for all group members. 33 out of the 34 groups verbally expressed that all members would invest equal amount of money into the group fund. 27 groups came to the consensus that all members would invest the full $16 to the group fund.

However, not all members kept their word and the amount of *defection* is the difference between the amount that the participants promised and the actual amount that they invested. The amount of defection has a strong negative correlation to the cooperation level. The relationship is not a perfect linear relationship due to the six groups that decided that all members should invest the same amount but decided on a partial amount. For example, if the group came to a consensus that all members will invest \$10 out of the \$16 into the group fund and kept their promise, the defection value would be zero. However, the cooperation rate would be \$40 out of the maximum of \$60. We used the sum of the individual defection values as the group measure, which ranges from \$0 to \$64. The defection amount is \$0 when all members keep their promises independent from how much the promise was, and the defection amount is \$64 when all group members promised to invest the full amount but everyone ended up investing \$0.

3.1.3 Results

We observed all the features of communication detected by the Sociometric badges (section 2.2.1). However, the most apparent and consistent relationship that we find is that the number of turn transitions per second have a positive correlation with the total amount of cooperation (r=0.37, p<.05, N=34). Further observation of the data shows that there are two apparent outliers in the data: 32 groups had an interactivity level less than 0.66 turns/sec, where as two of the groups had an interactivity of 0.57 turns/sec and 0.71 turns/sec. These values were more than $2\times\sigma$ (σ=0.15 turns/sec is the standard deviation) outside of the distribution mean (0.14 turns/sec). Excluding these data, we see an even stronger relationship of turns/sec and performance (r=0.44, p<.05, N=32). These results indicate that groups with higher interactivity level, which can be estimated by the higher number of turns per second, tended to have higher cooperation rate. The corresponding relationship holds for defection as well: groups with higher turn transitions per sec tended to have lower defection rate (r=-0.37, p<.05, N=34). Hence, we see that groups that had more interactions in the 10-minute conversation tended to have higher cooperation rate and lower defection rate after the conversation ended.

The communication pattern and the measured cooperation level has a temporal sequence: the groups had 10 minutes for discussion first and then later made their decision. However the correlation between the two measures does not necessarily indicate causality. It may be that group members who have higher trust among themselves tend to have more turn transitions, or it may be that groups that have more interactions build higher group identity and trust during the conversation that leads them to be more cooperative. This question of causality will be addressed in Chapter 4.

The relationship between interactivity and cooperation is especially interesting when we analyze the content of speech during the conversation. Surprisingly, the verbal content of the conversation did not predict this cooperation level. As mentioned earlier, we saw that 33 out of the 34 groups came to the consensus that they would invest equal amount into the group fund. However, that is not what happened: only 20 out of the 33 groups kept their promises. One or more members in the other 13 groups decided to break their promises. Hence listening to what the group members were saying did not predict the outcome, but just looking at the number of turns per second had predictive power over the decisions of group members after the conversation had ended.

> *Conclusion: Cooperation level of a group has a positive correlation with the interactivity level of the group.*

3.2 Information-Sharing Task

A second task was studied to verify that whether the strong relationship between communication pattern and the performance holds for a wider variety of tasks. As the second task, we used a variation of a hidden-profile task, which measures how well the group members shared the information. The group cannot successfully perform the task unless they pool all the information that the members individually hold. We apply the format of a 20-questions game to the hidden-profile task to have a quantitative measure on how well the information is shared among members. The task is a 20-questions game, in which the possible answer space is strictly confined and equally divided among the members. All information from all members were required for the group to generate more efficient questions. The optimal strategy of problem solving was informed to all groups, as we wanted to measure the level of how well the group cleared the information and eliminate the noise caused by individual knowledge on various strategies.

The procedure follows: each member was given a sheet of paper with a list of 10 people (possible answers) along with three attributes of their personal information, which were height, weight, and a test score (an example of such list is shown in Table 3.2) . Each member's sheet had a non-overlapping set of possible answers; hence there were 40 possible answers in total among the four members. Basically, it was a simplified hidden profile task with no shared information. The goal of the game was to correctly guess the one person that the experimenter is thinking out of the 40 possible answers. Groups discussed to generate a yes-or-no question which narrows down their answer space. When a question is generated, the experimenter answers the question by either a yes or a no, after which the groups continue their discussion to generate the next question based on the answer that they heard. This process was repeated until the group came to the correct answer. The number of yes-or-no questions that the group needed to come to the correct answer was the inverse-measure of the group performance. One of the participants was chosen as a task coordinator immediately before the task starts. The task coordinator's role was to be the channel of communication between the subjects and experimenter. For the first question, up to 4 minutes were provided for question generation, and 2 minutes were provided for the following questions.

The optimal strategy to quickly arrive to the answer was to ask yes-or-no questions that would narrow down the possible answer space in half. This strategy would guarantee that groups could come to the correct conclusion within $log_2(40) = 5.32$ number of questions. This strategy was informed to all participants before the task started. Hence, all groups aimed to generate a question that divides the answer space into half. In order to generate this optimal question, they needed to communicate verbally to correctly understand the distribution of the three attributes of the possible answers. If one more members withheld the information that they had, the group would have a biased understanding of the answer space which resulted in asking questions that did not halve the possible answer space. The sociometric badge data was captured and analyzed during the time of discussion of each question generating phase. Hence, we observed the communication pattern when the groups were sharing information and generating questions, and compared that to the efficiency of questions that the group came up with.

Person ID	Height	Weight	Grade
A	5'1"	99	A
B	6'0"	201	A-
C	5'6"	272	C+
D	5'7"	150	C
E	5'7"	183	A-
F	5'6"	134	A
G	6'9"	270	C
H	7'4"	330	B
I	7'4"	310	F
J	4'11"	97	C+

Table 3.2: A sample possible-answer list that one of the participants received.

Table 3.2 shows a sample possible-answer sheet that one of the participants received. If one only considered this particular list, an optimal question might be "Is the person of interest taller than 5'8"?", as this question would narrow down the answer space into half. However, to increase the overall group performance, the group needs to take consideration of the whole answer space which was the size of 40. If it turns out all of the possible answers on the other three lists were shorter than 5'8", then the same question would be a very inefficient question as it would not eliminate any of the possible answers on those lists. Therefore, it was critical to communicate with all the members to have an accurate understanding of the whole answer space to generate efficient questions.

3.2.1 Related Work

A hidden profile task is a group task where a superior decision alternative exists but its superiority is hidden from individual members because they each have only a portion of information that supports the superior alternative [74]. No group member can detect the best solution on the basis of her or his individual information prior to discussion; it can only be found by pooling the unshared information during group discussion.

Stasser and Titus found that decision-making groups can potentially benefit from pooling members' information, particularly when members individually have partial and biased information but collectively can compose an unbiased characterization of the decision alternatives [75]. However, they found that group members often fail to effectively pool their information because discussion tends to be dominated by (a) information that members hold in common before discussion and (b) information that supports members' existent preferences. Hence, this model was adopted in our task by providing a partial and biased information answer space to each member. The task was simplified by having all hidden information and no common information among the members. The answer space was chosen to be a symbolic space so that no member would have prior knowledge or preferences.

Cramton found that maintaining mutual knowledge is even harder for distributed groups [20]. Among other reasons, she found that failure to retain contextual information, difficulty in communication and understanding the salience of information, and difficulty interpreting the meaning of silence made it more difficult for groups to clear information and maintain mutual knowledge. Hence, information clearing is more challenging for distributed groups.

3.2.2 Methods

Experimental Setup

We conducted a laboratory study in which the setup was quite similar to that of the cooperation study. Again, the goal was to examine the relationship between communication patterns and the group performance. We recruited four participants for each session who were each asked to wear the sociometric badge throughout the whole duration of the experiment. Unlike the cooperation experiment, only distributed groups were observed in this study. All groups were separated into pairs, with audio communication supported between the pairs.

We had two different controlled conditions and two experimental conditions. In the first control condition, we did not provide any kind of visualization to the group, there was plainly nothing on the table providing feedback. The second control condition was a still feedback condition, where the individual display on the table was kept still for the whole

no feedback	still feedback	group feedback	indiv. feedback
8	8	18	16

Table 3.3: Number of four person groups included in the analysis of the information-sharing task.

duration of the time. In the two experimental conditions, we tested the group-level and individual-level feedback introduced in section 2.2.3. Detailed reasoning of the differences of these feedback will be later discussed in Chapter 4. In this section, we included the data from all four conditions to find the general relationship between communication patterns and the efficiency in information sharing.

Participants

We recruited 50 groups of four subjects each, total of 200 participants. Sociometric badges were provided to all subjects to measure group communication patterns. The total number of groups included in the analysis is shown in Table 3.3.

Tasks and Procedures

Participants were separated into pairs and seated in two different rooms. Participants were given instructions of the task along with the optimum strategy. Examples were given to make sure each participant had full understanding the task and the optimum strategy. Before the task, participants were asked not to talk to each other, even to the participants in the same room. Once all participants understood the study, the lists of possible answers were given to the participants. This list was different for each participant and they were non-overlapping. The participants were later allowed to talk about their list, but they were never allowed to show this list to other members. All members were given a short time (1-2 minutes) to look over the list individually before starting the conversation with other members.

Groups were given up to 4 minutes to generate their first question, and an additional 2 minutes per following questions. After the group came up with a question, the task-coordinator of the group would raise his/her hand to notify their question to the experimenter. The experimenter replied via speakers that were connected to both rooms. The experimenter recorded the start and end times of each question generating phase, as well as the question that the group generated.

Performance Measures

We can measure the performance of each question that the group came up with. For each question, groups can generate more or less efficient questions. A question dividing the possible answer space into half is the most optimal question, whereas a question dividing the answer space into an unbalanced ratio is a less efficient question. If groups are lucky a non-halving question may end up narrowing down more of the possible answers, but this would only happen in the unlikely case that the answer is in the smaller division. More likely, a non-halving question would increase the expected number of questions the groups have to use. Hence, all groups were asked to stick to the strategy of cutting the answer space into half in each question, which most groups followed.

We define *error* as the amount that each generated question deviates from the optimum question. Hence, it is the inverse measure of efficiency ($error = 1 - efficiency$). We measure the amount of error by looking at the ratio between the sizes of the cut answer space to the optimum, which is half the original. In an answer space of a size of 40, a question dividing it in to two lists of 20, has an error of 0. A question dividing the answer space into a list of 25 and a list of 15, has an error of $5/20 = 0.25$. A question dividing the answer space into a list of 10 and a list of 30, has an error of $10/20 = 0.5$. In the worst case, where the question does not divide the answer space at all, the error would be 1.

We chose to look at the error of the first question as an inverse measure of performance. There were three reasons behind this decision. First, the first question is the most challenging question as it has the largest answer space: 40 possible answers. Second, the efficiency

Number of questions used	5	6	7	8
Number of groups	9	19	18	4

Table 3.4: The distribution of groups by the number of questions they used to get to the correct answer.

in the following questions are dependent on how well the group did on the first question. Therefore, groups that did a bad job in the first question would have more difficulty in future questions just because they have a bigger answer space. Lastly, we discovered that, toward the latter questions, some groups tended to make guesses without following the strategy to halve the answer space. This phenomenon happened because there was an extra prize for the group that came to the correct answer with the least number of questions. Hence, groups were taking big risks toward the last one or two questions. In these cases, we expect that the communication pattern would not drive the performance as groups were intentionally making question that were inefficient. Due to these three reasons, we used the performance of the first question as an estimate performance of information sharing. Accordingly, we compare the communication patterns of only the first four minutes corresponding to the first question generating phase to understand the relationship between performance and communication patterns.

The number of questions used to come to the correct answer ranged from 5 to 8, an average of 6.3 questions (Table 3.4). A few groups were not able to come to the answer at all, which only happened when one of the participants accidentally eliminated the correct answer by mistake. Theses groups were not included in the analysis and is not included in Table 3.3. The efficiency of the first question ranged from 0.3 (dividing the answer space as 6:34) to 1 (dividing the answer space as 20:20). The mean efficiency was 0.83 and the standard deviation was 0.19.

3.2.3 Results

As in the cooperation task, we find very strong relationship between communication patterns and performance. Yet the relationship is not identical to that of the cooperation task. We actually do not find strong relationships between the performance and any of the measures mentioned in section 2.2.1. Instead, the analysis of how similar these measures are among the group members shows very strong and consistent relationships. The similarity among the group members is calculated as an inverse measure of the standard deviation among the normalized features among the individuals. We chose to normalize the values when calculating the similarities as we were interested in the ratio among the members, not the absolute values. Had we used the SD of the absolute values, groups that had higher absolute values would have been penalized in their SD values, even though the ratio among the members might have been was similar. An example of calculating a level of similarity follows. If the four members of the groups had a movement energy of 0.08, 0.12, 0.06, and 0.05; the normalized values against the largest value would be 0.67, 1.00, 0.50, and 0.42. The standard deviation of these values is 0.26. This group would have a higher similarity in movement behavior than a group who has a standard deviation of 0.30, for example.

We observed this similarity in behavior for all the badge data and found a consistent trend of a positive relationship between similarity in behavior and performance. This results reveals that the performance tends to be higher in groups in which the members have a more similar style of behavior. This positive relationship hold for the similarity in body movement energy ($r=0.24$, $p=.09$, $N=50$); the similarity in speaking speed ($r=0.30$, $p<.05$, $N=50$); the similarity in speaking time ($r=0.32$, $p<.05$); and the similarity in turns/sec ($r=0.30$, $p<.05$, $N=50$).

As a parallel measure, we look at evenness of turn transition among the members, an inverse measure of centrality. Centrality is calculated using a method commonly used in social network analysis, adapted from Leavitt's method [53]. It takes into account the number of turn transitions between each pair of participants, and investigates the degree of whether there is a central person in the group's turn-taking patterns. Centrality is the ratio of the number of turn transitions involving a central participant to the number of turn transitions that does not involve the central participant. The central node is defined as the node where the sum of weights of all connecting vertices is the highest. The mathematical equation of centrality of a 4-node graph as in Figure 3-3 is:

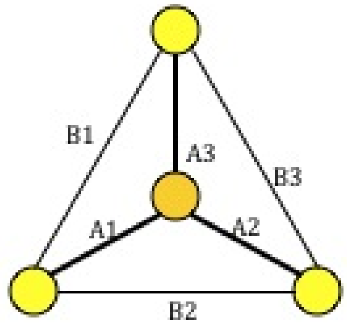
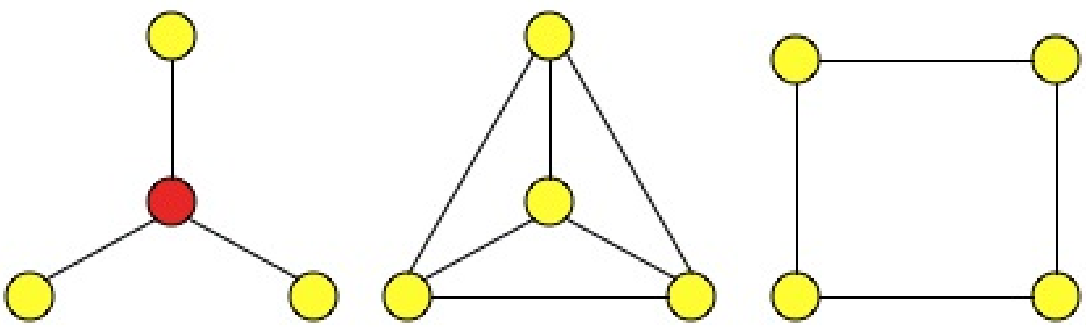


Figure 3-3: The 4-node graph to demonstrate how to calculate centrality



(a) centrality=1 (b) centrality=0 (c) centrality=0

Figure 3-4: Centrality values of extreme turn-transition patterned graphs

$$Centrality = \frac{(A1 + A2 + A3) - (B1 + B2 + B3)}{(A1 + A2 + A3)} \tag{3.1}$$

The centrality value is 1 when one member is involved in every turn transition (Figure 3-4a), and the value is 0 when all members are equal (Figure 3-4b, 3-4c). Hence, the inverse measure of centrality can be labeled as the *evenness in turn transitions* among members.

Data analysis shows that groups with more even turn transitions among the members, tended to have higher efficiency in information sharing (r=0.32, p<.05, N=50). So groups that did not have a central person controlling the turn transitions, tended to have higher performance.

These results show that the more similar the group members behave with one another, the less likely were they to make errors in question generating, leading them to be more efficient in coming to the correct answer. This finding is quite interesting as we see that the synchrony of behaviors seems to indicate higher performance. For example, groups had higher performance when all members spoke fast or if all member spoke slow. On the other hand, if some members spoke slow and other spoke fast, then the group tended to have lower performance.

This finding is in line with the interactional synchrony literature. Scheflen found that people in a group often mirror one another's posture and that those who share a posture usually share a viewpoint as well [71]. This synchrony of behavior has been shown to have a correlation with rapport, listener engagement, and affiliation among members [17, 36, 43]. This synchrony among members is facilitated through interactions among the members. Richardson, Marsh, and Schmidt found that verbal interaction alone does not provide a sufficient medium for unintentional coordination to occur [69]. Hence, we can expect that this development of synchrony is more difficult for distributed groups communicating through audio only.

The relationship of synchrony and performance in our data is from distributed groups. Thus, even though all groups were separated, groups were somehow able to develop some level of synchrony among the members. And the groups that were better in doing so, tended to have higher performance in the information-sharing task. We want to point out that this trend is found not only in the speech patterns but is also found in body movement energy. Even though the participants did not see each other, the communication allowed the alignment of their body movement amount. Groups, of which the participants in one room moved as much as the participants in the other, were more likely to be efficient in information sharing.

These measures have predictive power over the overall efficiency of the task. The similarity in body movement variance (β_1 =0.86), the similarity in speaking speed (β_2 =0.95), and the evenness in turn transition (β_3 =0.41) predicted 30% of the variance in group efficiency (r^2=0.30, p<.001, N=50). Hence, just by looking at the similarity of the behavior among the members, we can predict 30% of performance in the information-sharing task. As in the cooperation task, I am not yet stating causal relationships, just stating that there is a temporal sequence in the relationship.

> *Conclusion: The efficiency in group information sharing has a positive correlation with the similarity of behavior among the group members.*

3.3 Discussion

The two tasks have different patterns of communication that lead to high performance: higher number of turns lead to higher cooperation and higher similarity in communication patterns lead to higher information-sharing efficiency.

In the cooperation task, our finding agrees with earlier studies where researchers found that groups that communicated through richer communication medium tended to have higher cooperation level [13, 64]. Additionally, Kleji et al. showed that collaborations over richer communication medium tended to have higher number of turns [79]. Our study results connect these two former findings and reveal that the reason why cooperation is higher for groups using richer communication medium is because richer medium facilitates more frequent turns for groups.

In the information-sharing task, we see that the similarity of behavior leads to higher performance. This is in line with work on collective intelligence, where the equality in the number of speaking turns by group members is found to have a positive relationship with the performance in a wide variety of tasks [84]. Similarly, Kim et al. found that the equality in speaking time predicted the interest level of couple shopping for furniture [45].

It is interesting to see that Wooley et al. found a common group measure, which they label collective intelligence, and this measure correlates with the performance of a variety of tasks including a brainstorming task, two group reasoning tasks, a group planning task, and a criterion task [84]. This collective intelligence measure correlates with the equality in the number of speaking turns by group members. Therefore, similarity of behavior seems to be a predictor for the performance of many tasks including the information-sharing task introduced in this chapter. However, the same factor did not predict the performance in the cooperation task. Instead, the total number of turns was the strongest predictor. Additionally, in a constrained brainstorming task, we found that average number of simultaneous speakers was the main predictor of the number of ideas generated [26], a factor that did not show up in either of the two studies introduced in this chapter. Hence, we conclude that there exist a commonality in the relationships between communication patterns and performance in tasks within a similar range, though the commonality is not found in all types of tasks. Moreover, the relationship is altered when the tasks' characteristics are changed.

3.4 Conclusion

From laboratory studies of two very different tasks, we verify that communication patterns measurable by the sociometric badges indeed have a strong relationship with the task performances. Aligned with Hackman and Vidmar's work [32], we see that the characteristics of a successful communication pattern differed for the two tasks: for the cooperation task, higher interactivity predicted performance and for the information-sharing task, the similarity in behavior among the members predicted the performance.

We acknowledge that this strong relationship may not be found in all types of tasks. For example, in an earlier task of a regular 20-questions tasks, we found that there were no significant relationship between the sociometric data and the group performance [46]. In that particular task, we found that the expertise of individual participants and pure luck had a stronger impact on the performance. Hence, the pattern of communication among the members had little impact on their performance. Therefore, our findings may not be generalizable to all types of tasks, but our study results indicate that it may be applicable to a wide range of tasks that are highly dependent on group collaboration.

The strong relationship between communication patterns and performance gives us a basis for hypothesizing that influencing the communication patters will result in a change in performance. Understanding the pattern of behavior that leads to successful performance allows us to better design the visual feedback, which can control the direction of change that should be encouraged. The effect of this feedback is examined in the next Chapter.

Chapter 4

The Effect of Sociometric Feedback on Group Communication Patterns and Performance

In the previous chapter, the communication patterns measured by the sociometric badges were found to have a strong relationship with the group performance. Higher interactivity correlates with higher cooperation level, and more similarity in behavior among the members correlates with the efficiency in information sharing. In this chapter, we test the effectiveness of a real-time sociometric feedback as an intervention on both the communication pattern and group performance. Real-time data collected by the sociometric badges is used as a mean to inform groups how they deviate from the encouraged norm, assisting their communication patterns adjustments. We first observe if there is a change in communication patterns as a result of feedback and then observe if that change leads to a change in the group performance. Examining the effect of feedback on both communication patterns and performance, we can provide insight on the causal relationship between the two. This work is done in collaboration with Prof. Sandy Pentland.

The two tasks introduced in chapter 3 are revisited. To test the effect of sociometric feedback, we compare a control setting with no feedback, with an experimental setting where there were four mobile phones sitting in front of the table, facing each participant. We used the sociometric feedback described in section 2.2. The sociometric feedback visualized the communication patterns of groups in real-time showing how they are deviating from a norm. We investigate the effect of sociometric feedback on both communication patterns and the group performance.

4.1 Related Work

Our approach is to influence the group communication patterns to see if that leads to an improvement in performance. To change the communication patterns of groups, we use automatic measurement of communication patterns and real-time feedback. Many of the previous work have created novel interfaces that provided feedback on group communication patterns, with an emphasis on the design aspect of the feedback with little analysis on its impact [7, 10, 52].

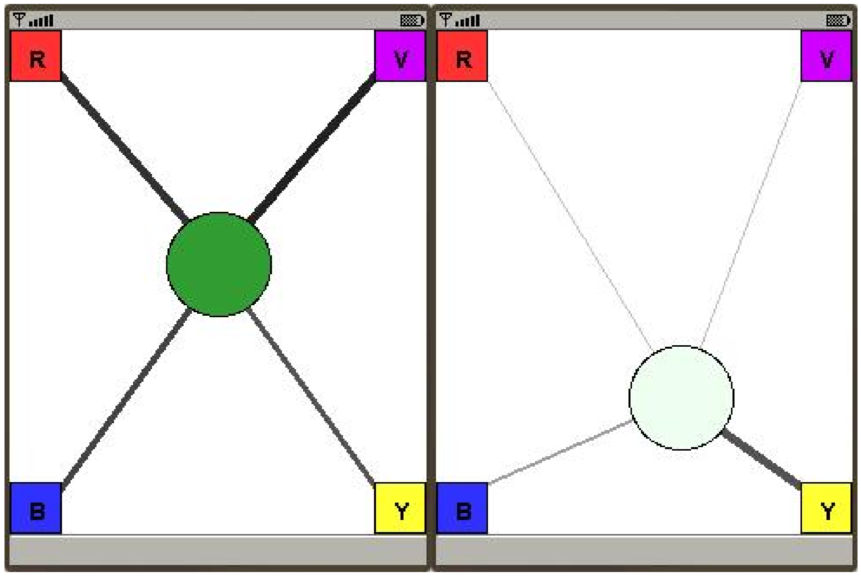
There are a few examples where the research has focused on measuring the changed behavior as a result of feedback on group communication patterns. Dimicco et al. measured the speaking time of each participant and visualized it as a bar graph on a share screen with the intent to balance the amount of participation [25]. They showed that the feedback effectively made the over-participators speak less, but did not make the under-participators speak more. They report the effect of the feedback on multiple subjective measures, but did not find effect in the objective performance of the task. Leshed et al. aimed to change text-based distributed collaboration. They showed language-based feedback on a chatting system using a peripheral visualization [56]. This made participants express more agreements toward each other and focus more on their language use. Terken and Sturm measured the speaking time and gaze behavior, and provide visual feedback about these aspects to the meeting participants through a peripheral display [78]. The authors showed that feedback influenced the behavior of the participants in such a way that it made over-participators speak less and under-participators speak more, though there were little effect on gaze behavior.

None of these work focused on the effect of feedback on the objective measures of performance. However, in the previous chapter we found that group communication patterns and performance is tightly linked in certain tasks. Therefore, we expect sociometric feedback to have a significant impact on group performance in these target tasks.

4.2 Cooperation Task

We examine the effect of sociometric feedback on the performance of the social dilemma task introduced in 3.1. In section 3.1, we saw that the cooperation level of the group had a positive correlation with the interactivity level of the group (number of turns per second). We hypothesize a causal relationship between the two; hence if the sociometric feedback increases the interactivity level of the group, we can expect an increase in cooperation level.

There have been efforts to overcome the effects of distribution in social dilemma tasks. Providing opportunities for the members to socialize before the tasks have consistently shown to be helpful for cooperation. This effect was apparent in both situations when the socializing was in face-to-face [70] and when mediated by a computer [85]. Orbell and Kragt found that groups with an opportunity to have task-related discussions had a greatly increased level of cooperation, compared to groups that did not get any chance to talk [64]. This was due to the fact that discussions often led to shared commitments on cooperation. Not all members kept their commitments, but having a commitment made it more likely for group members to make cooperative decisions. Nguyen and Canny found that correcting the spatial distortions of nonverbal cues during the task-related discussions improved the level of cooperation even more, making video-conferencing groups have essentially equal performance as groups that are co-located [60]. Hence, prior work shows that an improvement in communication between members can improve their cooperation level, signaling a causal relationship.



(a) Balanced and interactive (b) Unbalanced and non-interactive

Figure 4-1: Group-level feedback visualization for a four person group. An example of a visualization of a group when (a) every one's participation is balanced with high interaction and (b) one person is dominating the conversation with low group interactivity.

4.2.1 Hypotheses

The group-level feedback introduced in section 2.2.3 is designed to increase the interactivity level of the group. The central circle becomes greener when groups have higher interactivity level, and the circle becomes paler when groups have lower interactivity level (Figure 4-1). We believe that by informing groups how much they deviate from the form (the degree of greenness) will encourage groups to have higher interactivity level,

We believe that this effect of the sociometric feedback will be found in both co-located and distributed groups but the effect size will be larger for distributed groups. Our reasoning follows. First, distributed groups have a stronger need to reconstruct the functionality of social signals. Co-located groups already have enough channels for members to provide feedback on each other's behavior. Examples of feedback include staring, looking bored, or even a kick underneath the table in extreme cases. For distributed groups, these channels are limited, making it harder for group members to understand the current balance or the interactivity level of the group. Hence, sociometric feedback will have a greater impact on distributed groups. Moreover, by restoring the functionality of the social signals, the behavior of distributed groups may become more like co-located groups. The second reason we think the sociometric feedback will have a stronger effect on distributed groups, is that there is more room for improvement in distributed groups. Van der Kleji et al. found that the distributed groups took fewer turns, a factor found to have a direct relationship with group performance [79]. Hence, we might see stronger effect of sociometric feedback on distributed groups compared to co-located groups. Therefore, our hypothesis follows.

> *The sociometric feedback increases the interactivity level of groups, especially in distributed groups. (H4-a)*

We believe that the increased interaction will result in a higher cooperation level. Prior work such as [60] and [64] seems to hint that there is a causal relationship between communication patterns and performance. Hence, we believe that groups having more number of interactions will be more likely to build stronger group identity and trust among members during the conversation, leading to higher cooperation level.

We believe that the effect of feedback on performance will be stronger on distributed groups. This hypothesis will be supported if H4-a is verified: if interactivity drives performance, the larger change in interactivity will result in larger change in performance. Moreover, there exists a ceiling effect in the cooperation level for co-located groups. Bos and his colleagues [13] discovered that there is very little headroom for effect for groups collaborating face to face: the group's cooperative level is close to maximum even in their first encounter. However for distributed groups with only audio communication, Bos found the cooperation rate is lower than 70% of the maximum, allowing 30% of headroom for effect. Hence, we posit that sociometric feedback will increase the level of cooperation, and the size of effect will be greater for distributed groups.

> *The sociometric feedback increases the cooperation level of groups, especially in distributed groups. (H4-b)*

	# of groups w/o Feedback	# of groups w/ Feedback
Co-located first	13	9
Distributed first	14	9

Table 4.1: Number of four person groups included in the performance analysis of the cooperation task.

The verification of these hypotheses will allow further articulation about the causal relationship between communication patterns and performance. This will be dealt in section 4.4.

4.2.2 Methods

To examine the relationship between communication patterns and group performance, we compare a controlled condition (no feedback) with an experimental condition (with sociometric feedback) in the social dilemma study introduced in section 3.1. The feedback used was the group-level feedback introduced in section 2.2.3. We recruited 45 groups of four subjects each, total of 180 participants (99 male, 81 female, mean age = 29.4, SD = 10.0). All participants were asked to wear sociometric badges throughout the whole duration of the experiment. Due to equipment failure, one of the badges did not collect audio data in the first few experiments. The sociometric data collected of these sessions were ignored. In addition, the performance data of these sessions in the feedback conditions were ignored as the feedback presented using this badge would not have been accurate. However, the performance data of the no-feedback condition sessions were included in the analysis as the decisions of the subjects were not affected by the badge malfunction. The total number of groups included in the analysis is shown in Table 4.1 and Table 4.2.

In the experimental condition, all four participants received the group-level feedback on mobile phones. The visualizations on the 4 phones were identical as they were showing information about the whole group with a minor change of orientation. In the control setting, even though no feedback was given to the participants, their communication patterns were still measured by the sociometric badges. Also given the consent of all participants, the

	# of groups w/o Feedback	# of groups w/ Feedback
Co-located first	8	9
Distributed first	8	9

Table 4.2: Number of four person groups included in the communication patterns analysis of the cooperation task. The number if different from Table 4.1 due to a badge malfunction.

session was video recorded using two webcams in the corner of the rooms. Additionally, participants were informed of the norm that they should follow (balance in participation and higher interactivity) and were told to stay close to the norm. Therefore, in both control and experimental conditions, participants were aware that they were being observed and measured, and that they should follow a specific norm to improve their performance. The only difference was that the experimental conditions had a constant reminder of that norm, and an indication of how much the group is deviating from that norm.

Each group participated in two rounds: once with all group members co-located in one room; and once separated into pairs in two different rooms (Figure 3-2). The sequence was counter-balanced. When in the distributed setting, the participants were not able to see the participants in the other room and were only allowed voice communication. As the experiment was a between-subject study, when groups moved from one condition to another, the experimental conditions were kept constant. Thus, the groups with feedback moved with their feedback display when they moved rooms. However, the data of the two rounds were combined in the analysis: the average value of the two rounds was used for the analysis of both the communication patterns and the performance. This decision was made due to the strong relationship between the communication patterns and the cooperation level: the communication patterns and the performance of the second round was strongly dependent on that of the first round (especially since the result of the first round was notified before starting the second round). Naturally, the second round's data was not independent from the first round's data, therefore it could not be considered as separate data points. We label the two different sequence conditions as "co-located first" and "distributed first", and the analysis includes the data from both rounds.[1] The effect by the change between

[1] The first round's data is uncontaminated data, hence using only the first round's data would have allowed

the two conditions is analyzed in detail in chapter 5.

To summarize, the study was a 2x2 between subject study, where the two independent variables were (a) the sequence of distribution (co-located first or distributed first) and (b) the existence of sociometric feedback.

4.2.3 Results

Effect of feedback on communication patterns

We see clear differences in communication patterns between the controlled and experimental conditions. To list a few that stand out: the feedback increased the speaking time of groups by 36% (mean=46% without feedback and 63% with feedback, $F(1,32)=8.06$ $p<.05$), and it also decreased the average body movement level by 7.6% (mean=0.37 without feedback and 0.34 with feedback, $F(1,32)=10.62$ $p<.05$). Hence, having the sociometric feedback increased the speaking time of the groups while making the groups move less.

The main characteristic of interest is the interactivity level (turns per second) of the group, as it has been shown to have a direct relationship with the cooperation level of the group. We did not find a significant relationship with the overall data (mean=0.21 turns/sec without feedback and 0.21 turns/sec with feedback, $F(1,30)=0.02$ $p=.87$, excluding outliers). However, if we only look at groups that were distributed first, groups with feedback tended to have higher interactivity level (mean=0.17 turns/sec without feedback and 0.24 with feedback, $F(1,14)=3.39$ $p=.087$, Figure 4-2). There was a significant main effect for geographical condition ($F(1,30)=11.48$, $p<.05$), and a significant interaction effect ($F(1,30)=8.29$, $p<.05$). Therefore, the results show that sociometric feedback did not have much of an effect on groups that were co-located first, but effectively increased the interactivity level in groups that were distributed first. In result, there became no significant difference between groups that were distributed-first and groups that were co-located first.

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a stronger statement regarding the geographical condition. Unfortunately, the effect of feedback exists in the same direction in the first round but is in the trend level (p=.14). We see a much stronger effect in the second round as the behavior and performance become more extreme as rounds are repeated (as found in [13]). Therefore, we chose to report the result using the combined data.

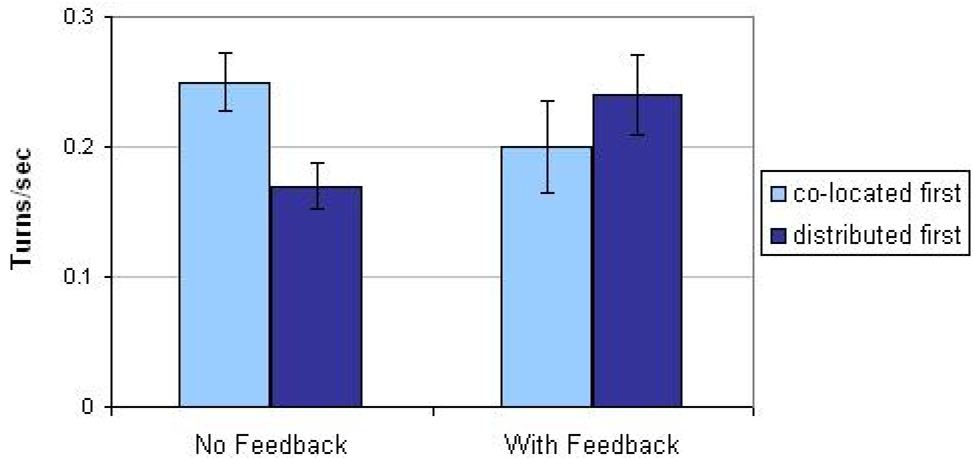


Figure 4-2: Interactivity level of groups in the four conditions. Feedback increased the interactivity level for groups that were distributed first.

The sociometric feedback tended to increase the interactivity level of groups that were distributed first. (H4-a)

Effect of feedback on Performance

The main question of interest is if this change in behavior results in a change in the level of cooperativeness. We examine the total amount of money invested in the group fund as a measure of cooperation. The maximum amount of contribution of an individual is $32 which is when the participant fully invested their $16 into the group fund both rounds. In the controlled conditions where there was no feedback, the cooperation level was significantly lower for individual in groups that were distributed first. But when feedback is provided we see that there was a significant increase in the cooperation level in groups that were distributed first (Mean = ($27.85, $23.29, $26.64, $28.69) for (co-first no feedback, dis-first no feedback, co-first with feedback, and dis-first with feedback), $X^2(3,176)=10.17$, $p<.05$, Figure 4-3). Hence, the sociometric feedback helped groups that were distributed-first to perform as well as groups that were co-located first. The main effect is not significant for both feedback ($F(1,176)=2.43$, $p=.12$) and geographical condition ($F(1,176)=0.86$, $p=.35$), but the interaction effect is significant ($F(1,176)=6.02$, $p<.05$). This result holds in the group

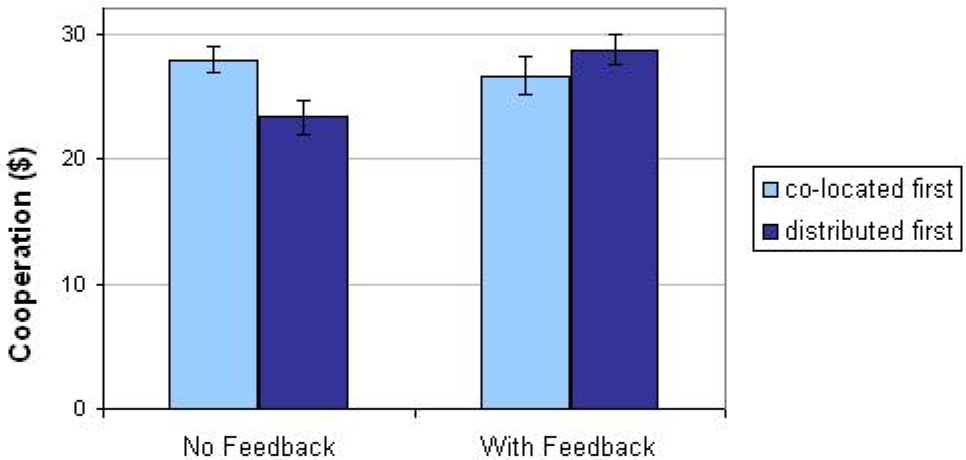


Figure 4-3: Cooperation level of individuals in groups in the four conditions (maximum value is $32 per individual, N=52,56,36,36). Feedback significantly increased the cooperation level for individuals in groups that were distributed first.

level, but the different is not significant due to the lack of power (X^2(3,41)=3.67, p=.30, Figure 4-4). The main effect is not significant for both feedback (F(1,41)=0.88, p=.35) and geographical condition (F(1,41)=0.31, p=.58), but the interaction effect is approaching significance (F(1,41)=2.17, p=.15).

Therefore, the sociometric feedback significantly increased the cooperation level of the distributed groups such that there is now no statistically significant differences between groups that started co-located or distributed. Due to the design of our study, the group performance had a linear relationship with the sum of their individual cooperation levels. As the performance data was non-Gaussian, we used a Kruskal-Wallis non-parametric test to examine these effects.

> *The sociometric feedback increases the cooperation level of members in groups that were distributed first. (H4-b)*

We observe similar effects of sociometric feedback on group identity and trust measured by post-task survey. The survey asked the group identity and trust of the members using a 5-point Likert scale. Comparing the four different scenarios, we can see that groups that

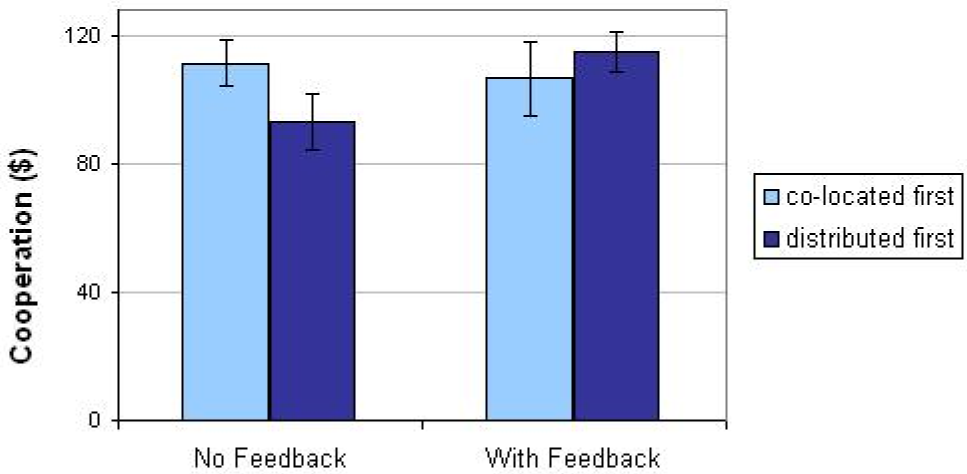


Figure 4-4: Cooperation level of groups in the four conditions (maximum value is $128 per group, N=13,14,9,9). Feedback tended to increase the cooperation level for groups that were distributed first.

were distributed first without feedback have a significantly lower group identity than the other three conditions (Mean = (3.67, 3.25, 3.63, 3.54), $F(3,29)=3.85$, $p<.05$). Whereas in the feedback condition, there are no statistical differences between co-located first groups and distributed-first groups. This means that the feedback had significant effects on groups that were distributed first causing them to have a group identity level similar to that of co-located groups. Similar results were shown in the level of trust. Again, the groups distributed first show much lower level of trust toward their group members than the other three conditions (Mean=(4.16, 3.22, 4.08, 3.92), $F(3,29)=3.98$, $p<.05$). However, there are no differences between the two conditions when feedback was provided. We can infer from the results that the sociometric feedback has a stronger effect on distributed collaboration, making their level of group identity and trust similar to that of co-located groups. Group identity and trust have very highly correlations ($r=0.78$).

4.3 Information-Sharing Task

In the previous section, we found that the feedback affected the communication pattern and the performance of cooperative tasks. The effect was significant in distributed groups, but minimal in co-located groups as the group already had a full channel of communication to provide feedback via social signals. Hence, for this following study we tested the effect of feedback only on distributed groups. In this section, we examine the effect of sociometric feedback on the information-sharing task introduced in section 3.2. We first examine the communication patterns while the group is participating in the information-sharing task, and then see if the change in communication pattern leads to a change in performance. Dennis and Kinney found that using media that offer more communication cues, led to faster decision making [23]. Therefore, we believe that if sociometric feedback provides more social cues, it may help groups be more efficient in their information sharing and faster in coming to a consensus in problem solving.

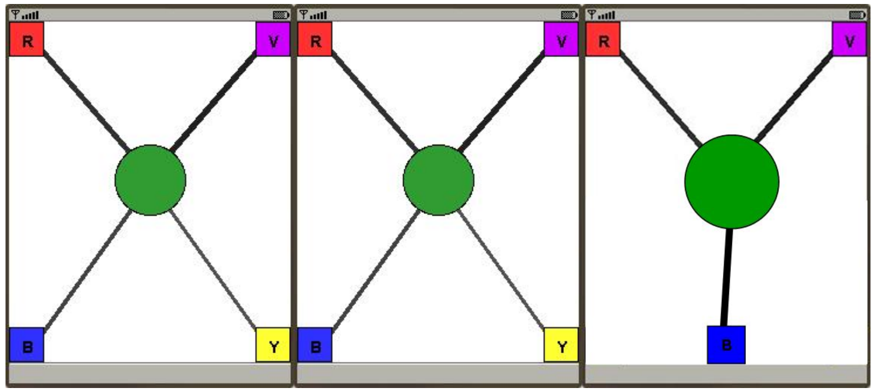
The task was introduced in section 3.2. In the section, we saw that the efficiency in information sharing had a positive correlation with the similarity of behaviors among the group members. We again hypothesize that there is a causal relationship between communication patterns and performance. Therefore, we hypothesize that if a sociometric metric feedback can increase the similarity in behaviors among the members, it will increase the efficiency of information sharing.

4.3.1 The Four Feedback Conditions

To further understand the effect of feedback on communication patterns and performance, we compare four different feedback conditions: (a) a no-feedback condition, (b) a still-feedback condition, (c) a group-level feedback condition, and (d) an individual-level feedback condition. The first two conditions are the control conditions and the latter two are the experimental conditions (Figure 4-5).

No Feedback Condition

The first condition is the base condition where there is no intervention to the group members. We measure their communication patterns and their efficiency in information sharing, but no real-time feedback is given about their communication pattern. Before the task, subjects



(a) No feedback (b) Still feedback (c) Group-level feedback (d) Indiv-level feedback

Figure 4-5: The four feedback that were compared. (a) No feedback as the first controlled condition, (b) a still image as the second controlled condition, (c) a live group-level feedback, and (d) a live indiv-level feedback.

are verbally instructed to follow the norm (balanced participation and high interactivity). But during the study, they do not receive any reminder of the norm nor do they receive feedback about their deviation from the norm.

Still Feedback Condition

In the second condition, we provide a still image of the group-level feedback as a constant reminder to the participants, that they should have balanced and interactive communication. The reason why we added this control condition was that there were questions regarding why the sociometric feedback was so effective. The sociometric feedback has two main functions: (i) a constant reminder to the group to follow a norm and (ii) its functionality of showing how much the group's communication pattern is deviating from that norm. The second functionality is the effect of feedback that we wanted to test, hence we separated the first functionality and include it as a separate condition. Even in the no-feedback condition, the participants were encouraged to follow the norm (balance the participation and be interactive) by the task instruction sheets and the verbal reminder of the experimenter. However, it was only a one-time reminder and did not encourage groups to change their behavior during the conversation. Hence, we decided to add an extra controlled condition, where the same mobile phone would be sitting in front of each participant to be a constant reminder that they should be balanced and interactive. But unlike the live feedback, the visualization was fixed to an optimal state, without showing live data (Figure 4-5b). Therefore, this is a controlled condition, where participants did not get information about their communication patterns, but were only given a still but constant reminder about the norm they should follow. By adding this condition, we can verify if the *sociometric* aspect of the feedback is the factor creating the effect. We believe that the effect resulting from the mere reminder will be much smaller than the effect resulting from informing the groups how and how much they deviate from the norm.

Group-level Feedback Condition

In the third condition, the group-level feedback introduced in section 2.2.3 was used (Figure 4-5c). Groups received feedback on the balance among the participants and the overall interactivity level of the group. In this feedback, each participant of a group saw the exact same information that other participants saw. The location of the circle encouraged the speaking time of each member to be similar. The similarity in speaking time is one of the features that had a positive relationship with the information-sharing efficiency; therefore we can expect an increment in the performance when this group-level feedback is provided.

The color of the circle encouraged groups to be more interactive (more turn transition per time). However, since it visualized a single value for all members, it did not necessarily encourage all members to be interactive. If a subset of the members were interactive, while the other members were not so interactive, the center circle would still be green driven by the high-frquency turn-taking of the subgroup. The overall interactivity of the group is encouraged to be high, however the similarity in behaviors among the group members in interactivity is not necessarily encouraged.

Individual-level Feedback Condition

The fourth condition uses the individual-level feedback introduced in section 2.2.3 (Figure 4-5d). Individuals received feedback on the balance of turn transitions that s/he had with each of the other group members. The location of the central circle encouraged each participant to have a similar amount of interaction with each of his/her group members, encouraging groups to have evenness in turn transitions. This measure had a positive correlation with the efficiency of information sharing. Hence the location of the circle will encourage groups to have a flat structure with no central person leading the discussion, increasing the evenness in turn transition, which may lead to higher performance.

The color of the central circle encourages each individual to be interactive. Unlike the group-level feedback, free-riding in the aspect of interactivity was not possible: the feedback showed how interactive *you* are, not your group. Hence, it encourages all members to have an interactive level approaching the optimal state (green). Therefore, we believe that the individual-level feedback, compared to group-level feedback, would have a stronger effect on creating a similar behavior among members, leading to higher performance.

> *The sociometric feedback increases the similarity of behavior among group members in distributed groups. This effect is stronger with the individual-level feedback than the group-level feedback (H4-c)*

> *The sociometric feedback increases the efficiency in information sharing of distributed groups. This effect is stronger with the individual-level feedback than the group-level feedback (H4-d)*

Validating these hypotheses will allow us to articulate the causal relationship between the communication pattern and performance. This articulation will be shown in section 4.4.

no feedback	still feedback	group feedback	indiv. feedback
8	8	9	8

Table 4.3: Number of four person groups included in the analysis of the information-sharing task.

4.3.2 Methods

We conducted a laboratory study to examine the effect of sociometric feedback on communication patterns and the group performance in the information-sharing task. Experiments were conducted on 33 groups of four subjects each, a total of 132 participants. The number of groups per feedback condition is noted in Table 4.3.

Participants were separated into pairs and seated in two different rooms and communicated over audio. Participants were given instructions of the task along with the optimum strategies. Once all participants understood the study, the lists of possible answers were given to the participants. This list was different for each participant and they were non-overlapping. Groups were given up to 4 minutes to generate their first question, and an additional 2 minutes per following questions. When the groups came to a consensus on the question to ask, the experimenter replied with the yes-or-no answer to the question that they generated. The task have been described in detail in section 3.2.2.

As mentioned in section 3.2.2, we chose to focus on the first question that each group generated: we measure the performance of the first question, and therefore only observe the communication patterns of the group while they were generating the first question. This duration was up to 4 minutes, and most groups used the full 4 minutes to generate their first question.

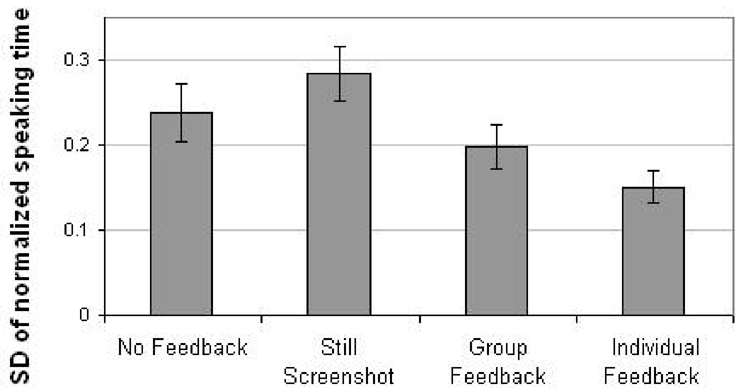


Figure 4-6: The standard deviation of normalized speaking time among members (N=8,8,9,8). Groups with sociometric feedback had higher similarity in their speaking time among the members.

4.3.3 Results

Effect of feedback on communication patterns

We see clear differences in communication patterns between the controlled and experimental conditions. We focused on the similarity of behaviors among the members, as they were shown to have a direct relationship with the performance of the information-sharing task. The standard deviation (SD) of the normalized behaviors among members was measured as the inverse measure of similarity in behavior.

The SD of normalized speaking time is 0.24, 0.28, 0.20, 0.15 for no feedback, still feedback, group-level feedback, and individual-level feedback respectively ($F(3,29)=3.85$, $p<.05$, Figure 4-6). The results show that the two control conditions have higher variance in speaking time among the members compared to to the experimental condition. Hence, groups with sociometric feedback had more similar talking time among the members. When comparing with the no-feedback condition, the effect was significant in the individual-level feedback (37% decrease in SD, $F(1,15)=4.89$, $p<.05$), but not in the group-level feedback (17% decrease in SD, $F(1,15)=1.59$, $p=.23$).

Similar results are found in speech energy. The SD of normalized speech energy is 0.32, 0.34, 0.28, 0.23 for the four conditions respectively ($F(3,29)=2.64$, $p=.07$, Figure 4-7). The

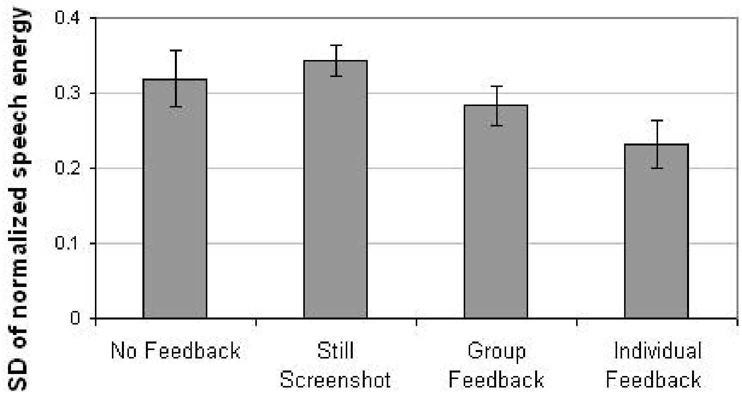


Figure 4-7: The standard deviation of normalized speech energy among members (N=8,8,9,8). Groups with sociometric feedback had higher similarity in their speech energy among members.

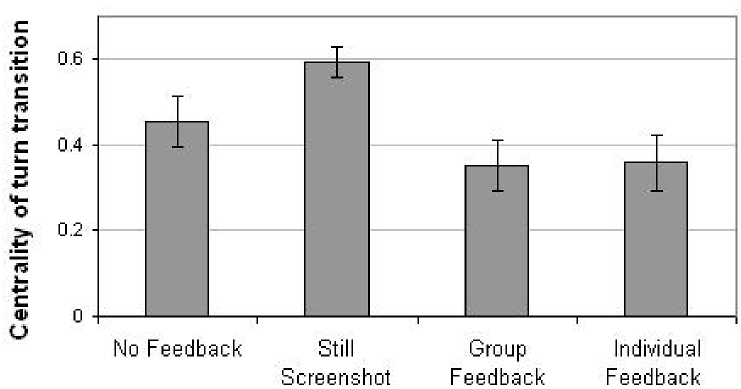


Figure 4-8: The centrality of turn transition among members (N=8,8,9,8). Groups with sociometric feedback had more evenness in turn transitions.

results show that the two control conditions have higher variance in speech energy among the members compared to the experimental condition. Hence, groups with sociometric feedback had more similar speech energy among the members. When comparing with the no-feedback condition, the effect was stronger in the individual-level feedback (27% decrease in SD, $F(1,15)=3.23$, $p=.09$) and less so in the group-level feedback (11% decrease in SD, $F(1,15)=0.62$, $p=.44$).

The same trend follows in the evenness in turn transitions. The centrality measure of the turn transitions is observed as the inverse measure of the evenness in turn transition. The centrality of turn transitions is 0.45, 0.59, 0.35, 0.36 for the four conditions respectively ($F(3,29)=3.93$, $p<.05$, Figure 4-8). The results show that the two control conditions have more of a central person in their turn taking behavior compared to the experimental condition. Hence, groups with sociometric feedback had more evenness in turn transitions among the members. The centrality measure for the two sociometric feedback conditions were lower than the no-feedback condition, however the difference was not significant: 23% decrease in centrality for the group-level feedback ($F(1,15)=1.47$, $p=.24$) and 21% decrease in centrality for the individual-level feedback (in SD, $F(1,15)=1.17$, $p=.30$). When compared to the still-feedback condition, the effect was significant for both the group-level feedback and the individual-level feedback: 40.1% decrease in centrality for the group-level feedback ($F(1,15)=11.3$, $p<.05$) and 39.6% decrease in centrality for the individual-level feedback (in SD, $F(1,15)=9.86$, $p<.05$).

Therefore, we see that the sociometric feedback increased the similarity of behaviors among members. We find this effect in multiple measures: similarity in speaking time, similarity in speech energy, and evenness in turn transition. As we expected, we see that the individual-level feedback had a stronger effect size than the group-level feedback in two of the three measures.

> *The sociometric feedback increases the similarity of behavior among group members in distributed groups. This effect tends to be stronger with the individual-level feedback than the group-level feedback (H4-c)*

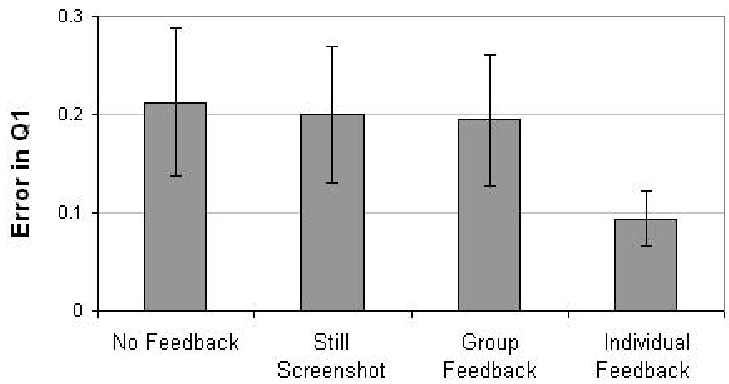


Figure 4-9: The amount of error in the first question of the information-sharing task (N=8,8,9,8). Groups with the individual-level feedback tended to have lower error when generating the first question.

Effect of feedback on Performance

We now examine if this increase in similarity in behaviors among the members led to higher efficiency in information sharing. We observe efficiency of the group in the first question generated. The average error that the groups made were 0.21, 0.20, 0.19, and 0.09 corresponding to the four experimental conditions ($F(3,29)=0.73$, $p=.54$, Figure 4-9). Comparing to the no-feedback condition, we see that there is almost no difference in efficiency for the group-level feedback condition (2% difference, $F(1,15)=0.03$, $p=.86$), but quite a big increase in efficiency for the individual-level feedback (15% difference, $F(1,15)=2.19$, $p=.16$). However, this difference is not significant.

We see larger differences when we examine the sum of errors that the group made to come to the correct answer. This finding is because the errors made in earlier questions have a negative effect on future questions, hence the effect is amplified toward the later questions. The average sum of error is 0.87, 0.77, 0.88, 0.30 for the four conditions ($F(3,29)=1.4$ $p=.26$, Figure 4-10). Comparing to the no-feedback condition, we see that there is almost no difference (2%) in sum of error for the group-level feedback condition ($F(1,15)=0.00$, $p=.96$). However, the sum of error dropped significantly (66%) for the individual-level feedback ($F(1,15)=6.77$, $p<.05$).

The results show that the individual-level sociometric feedback increases the efficiency in

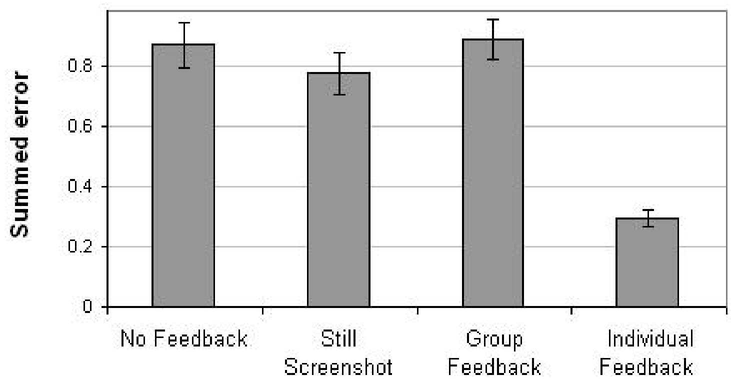


Figure 4-10: The amount of error summed over the whole problem solving period (N=8,8,9,8). Groups with the individual-level feedback have lower error sums in information sharing.

information sharing. However, no difference in efficiency was found in the group-level feedback conditions.

> *The individual-level sociometric feedback increases the efficiency in information sharing of distributed groups. (H4-d)*

4.4 Discussion

4.4.1 The Differences among the Four Feedback Conditions

Through the cooperation experiment, we have verified that the group-level feedback has a significant effect compared to the no-feedback condition. We further analyze the effect of sociometric feedback by comparing the four different feedback conditions introduced in the information-sharing task.

One of the main findings is that the still-feedback condition is not significantly different from the no-feedback condition. The only difference that we see is that the performance data of the still-feedback condition had a very large variance among the groups (SD of the summed error is 0.59, 0.99, 0.65, and 0.22 for the four conditions). The still feedback functioned as a constant reminder to follow the suggested norm. The lack of an effect of the still-feedback proves that the effect of the sociometric feedback arises from the ability to measure the communication patterns of the group and to show how they are deviating from the norm, not merely from its functionality to remind the norm.

Both group-level and individual-level feedback have an effect on various aspects of the communication patterns of groups, significantly varying from those of the no-feedback condition and the still-feedback condition. As mentioned in Section 2.2.3, there are significant differences in the two feedback designs. Related to the information-sharing task, the group-level feedback encourages balanced participation only, whereas the individual-feedback encourages balanced participation, equal interactivity level, and evenness in turn transitions. Therefore, we see that the individual-level feedback do a better job in increasing the similarity among the member behaviors, which results in a significant improvement in performance.

4.4.2 Causality Between Communication Patterns and Performance

Chapter 3 found that the communication pattern of groups and their performance have a significant relationship. Further, this chapter showed that a real-time sociometric feedback has an effect on both the communication patterns and the group performance. These results might hint at a causal relationship. We apply Baron and Kenny's Mediation model [6] to understand the role of communication patterns on the effect of feedback on performance. The sociometric feedback is considered the initial variable and the performance is the outcome. This chapter has shown that the initial variable (feedback) has an effect on the outcome (performance). However, we are hypothesizing that this effect is mediated by a mediating variable, which is the communication patterns of groups. Hence, the total effect of feedback on performance can be split into two aspects, the direct effect (c') and the mediated effect ($a \times b$, Figure 4-11). The Sobel test is applied to verify the significance of the mediation effect [73].

Let's first observe the information-sharing task. The individual-level feedback encourages

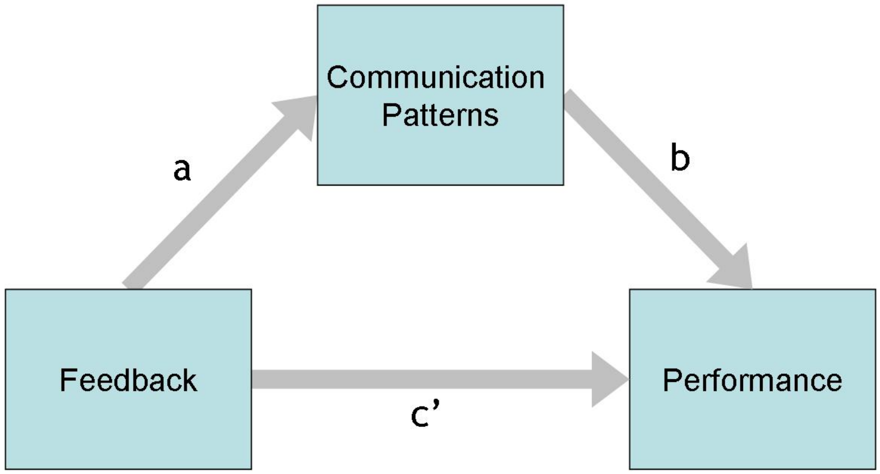


Figure 4-11: Baron and Kenny's mediation model

similarity in speaking time, similarity in interactivity, and evenness in turn transitions. Section 3.2 showed that these three factors all had positive relationships with group performance. In this chapter, we found that groups with feedback have significantly higher similarity in speaking time and evenness in turn transitions. Furthermore, these groups with feedback also achieve higher performance in their information sharing. There are no apparent reasons to believe that the feedback directly manipulated the information-sharing efficiency of groups: the feedback does not address any aspect of the answer or the strategy to get to the answer. Therefore, we may expect that the sociometric feedback changed the communication patterns of the group that led to the improvement in performance.

Let's apply the Baron and Kenny's test on this data to quantitatively verify this relationship (Figure 4-12). As the representative of the communication patterns, we used a linear combination of the three variables used in the linear regression in Section 3.2.3: similarity in body movement variance (β_1 =0.86), the similarity in speaking speed (β_2 =0.95), and the evenness in turn transition (β_3 =0.41). This communication pattern and the performance is z-scored. Results show that the feedback has a significant positive effect on the similarity of communication patterns (a=0.614, t=-2.09, p<.05). And the similarity of communication patterns have a significant positive effect on the performance even when controlled for the feedback (b=0.56, t=-4.47, p<.05). And the sobel test results verifies that this mediation ef-

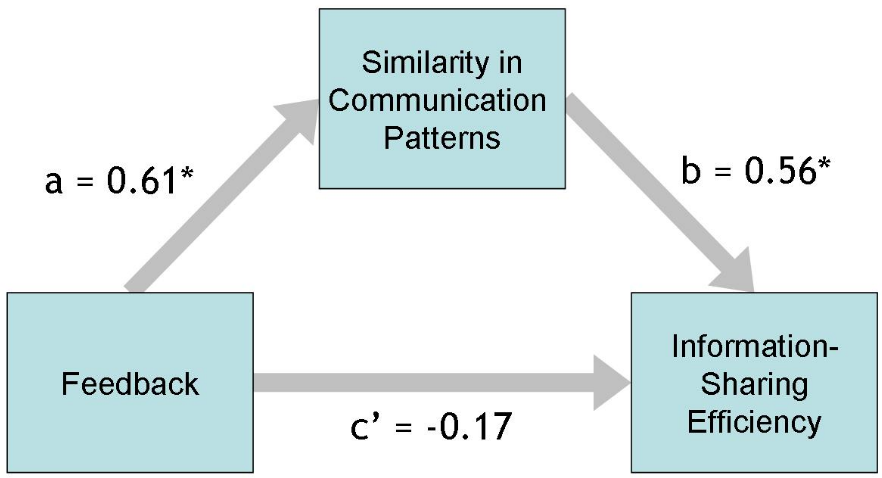


Figure 4-12: The mediation model in the information-sharing task (*:p<.05). The Sobel test results verifies a mediation effect (t=1.89, p=.058).

fect tends to be significant (t=1.89, p=.058). This finding indicates that the communication patterns significantly mediates the effect of feedback on the performance.

It is also interesting to see the direct effect of feedback on the information-sharing performance (c'). We see that this direct effect is not significant (c'=-0.17, t=-0.64, p=.52). Hence, the feedback does not have a significant effect on the group performance directly, but rather has an indirect effect mediated by the similarity of communication patterns. It is also interesting to see that the coefficient of this direct effect is a negative value. This result means that, though insignificant, the feedback tends to have a slightly negative effect on the information-sharing efficiency when only looking at the direct effect. The real-time feedback may have been a slight distraction to the group members causing a slight negative effect, but the overall effect is significantly positive as the feedback increases the similarity of communication patterns among members.

The cooperation task is a bit more complicated due to its multiple rounds. To examine the causal relationship, we only look at the first round's data as the second round's communication patterns are affected by many factors including the change in member distribution: the knowledge of the first round's result, and the fact that there was a previous round (the change in member distribution is examined in detail in the next chapter). The group-level feedback is designed to encourage higher interactivity, a feature shown to positively correlate with the cooperation level. This relationship still exists in a trend level when only examining the first round's data: interactivity is positively correlated to cooperation ($r=0.27$, $p=.12$) and negatively correlated to defection ($r=-0.32$, $p=.07$). In distributed groups, the performance of groups with feedback (\$93.8) tended to be higher than groups without feedback (\$90.7), though the difference was not significant ($F(1,32)=2.41$, $p=.14$). We see a very similar relationship with the information-sharing task: the feedback that aimed to change the communication pattern changed both the communication pattern and the performance. Applying the Baron and Kelly mediation model also shows that the cooperation task shows similar trends with the information-sharing task, but the relationship is not significant. The Sobel stat $t=0.20$, $p=.84$ with coefficients $a=0.07$ ($t=0.20$, $p=.84$), $b=0.44$ ($t=2.64$, $p<.05$), and $c'=0.19$ ($t=0.57$, $p=.57$). Therefore, the mediation effect approaches significance, signaling a causal relationship.

This finding is in agreement with some of the work done on communication and performance mentioned earlier. Orbell and Kragt found that groups with an opportunity to have task-related discussions experienced a greatly increased level of cooperation, compared to groups that did not get any chance to talk [64]. Hence, an opportunity to talk had a causal influence on the cooperation level of groups. Nguyen and Canny found that correcting the spatial distortions of nonverbal cues improved the level of cooperation [60]. Dennis and Kinney found that using media that offer more communication cues led to faster decision making [23]. Together with our study results, these examples show that some aspects of communication have a causal influence over the group performance.

4.5 Conclusion

In the previous chapter, we confirmed that the group performance strongly links to their communication patterns: cooperation level correlates with interactivity level and the information-sharing efficiency correlates with similarity in behavior among the members. In this chapter, we introduced an intervention in the form of a sociometric feedback. This sociometric feedback aims to change the communication patterns of groups in a direction that is beneficial to the group's performance. We measured the effect of feedback on both the communication patterns and the performance.

In the cooperation task, the study results show that the sociometric feedback encourages groups to have higher interactivity level. This effect led the group members to be more cooperative in their decision making. The effect was stronger for distributed groups, making the communication pattern and the performance of distributed groups no different from those of co-located groups. In the information-sharing task, we find that the sociometric feedback helps distributed group members to have a more similar style of behavior among themselves. This increase in similarity of behavior resulted in higher efficiency in information sharing. The effect was larger in the individual-level feedback, which was specifically aimed to increase the similarity of behavior.

We hypothesized that sociometric feedback is more helpful for distributed groups, as they have limited channels for social signals, limiting the members' ability to provide and receive feedback from one another. This limitation has made the communication in distributed collaboration dysfunctional, leading to suboptimal performances. This challenge of distributed collaboration allows an opportunity for sociometric feedback to improve performance. It is exciting to find that our study results confirm our hypothesis of sociometric feedback improving group performance, with the effect being larger for distributed groups. The results are promising, providing a new direction for enhancing distributed collaboration.

Chapter 5

The Effect of Sociometric Feedback on Change of Distribution

The previous chapter and previous work on distributed groups show that distributed groups differ from co-located groups. The difference was found in communication patterns, work processes, and their performance [13, 46, 38, 72]. This difference was due to the fact that none of the commonly used communication media can possibly support all social cues afforded in face-to-face collaboration [62]. Hence, the adjustment of behavior made by the groups differs depending on the amount of affordance offered by the communication medium. Most of these work focused on looking at between-subject differences: how does the average behavior of co-located groups differ from the average behavior of distributed groups? In this chapter, the focus is on the within-subject differences: when a group which was once co-located later become distributed, what happens to their communication patterns and performance and is this difference consistent among groups? In other words, I am focusing on groups that face *change of distribution* and observing the effect of feedback on these groups. The advance in technology has allowed more collaboration in distance and often the configuration of the member distribution can be quite dynamic. An off-site collaborator visiting or one's officemate working from home a few days are common examples showing how often change of member distribution can happen.

In the scope of this chapter, *the distribution of members* or simply *distribution* refers to the geographical "co-locatedness" of the members: whether the members are all in one room communicating face-to-face or if they are separated in different locations communicating over some technology. The *change in member distribution* or just *change in distribution* refers to the swapping of those conditions: co-located groups becoming distributed or distributed groups becoming co-located.

Generally, groups participating in a repeated task tend to show consistency in their behavior [57]. When the group is formed, the members interact with each other, developing a certain style of behaviors. The development of the group's behaviors is affected by many factors including the composition of members, goal of the group, medium of communication, and geographical conditions. Once a group's behavior is learned, repeated patterns can be observed from their subsequent encounters. For example, a group that tended to be very talkative may very likely be talkative in their future encounters performing the same task. This tendency can be labeled as social entrainment, the altering of social "rhythms" or patterns by external conditions, and the persistence of social "rhythms" over time [41].

But can we expect this consistency of behavior when the distribution of members changes? We can expect from earlier chapters that a change in member distribution will cause a general shift of behaviors in all groups due to the change in communication medium. But do we see a consistent shift of behaviors among the groups? In other words, when taking the shift into account, is each group's unique pattern of behavior still observable in their post-change encounter? For example, let's say that the change in member distribution tends to make groups speak less. Would a very talkative group in the pre-change condition, still be comparably more talkative than other groups that went through the same change? This question can be answered by measuring the predictive power of the pre-change behavior over the post-change behavior for the groups.

Next, I examine the effect of sociometric feedback on this phenomenon. Based on the result that sociometric feedback reduced the behavioral differences between co-located and distributed groups, I hypothesize that groups with feedback show consistent pre-change and post-change behavior even when they face change in member distribution. By bringing

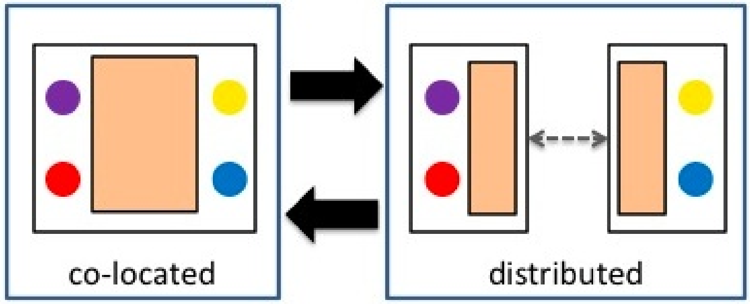


Figure 5-1: The distribution of members can change over time. Formerly co-located members can be distributed and formerly distributed members can be brought together.

back the functionality of the lost social signals, sociometric feedback can minimize the shift between the two conditions, eliminating the need for groups to adjust the behavior allowing groups to keep their unique learned behavior.

To answer these questions, we analyzed the cooperation experiment data of section 3.1 in which each group performs two rounds of a social dilemma task with a change in distribution between the tasks. Unlike the previous two chapters, in which we combined the two rounds of the cooperation task as a single data point, this chapter focuses on the difference between the two rounds. This work is done in collaboration with Prof. Pamela Hinds and Prof. Sandy Pentland.

5.1 Related Research

5.1.1 Social Entrainment

Social entrainment, or simply entrainment, has two main effects: (i) the within-trial effect and (ii) the across-trial effect. The within-trial effect occurs when an exogenous rhythm or signal is imposed on a group and the pattern of group behaviors is modified. The across-trial effect is the within-trial effect persisting beyond the initial trial, even when the situational conditions have been altered in a substantial way [41]. The within-trial effect can be generalized to an independent-variable-to-dependent-variable relationship. While as the across-trial effect is how much a dependent variable in the previous trial predicts that of the current trial. Viewing the member distribution as the external condition, the within-trial effect is the phenomenon of groups adjusting to their initial state of distribution, and the across-trial effect is the phenomenon of groups' behavior from the previous distribution state being persistent in groups even after a change in distribution. In the scope of this chapter, we will focus more on the across trial effect of entrainment.

Kelly and McGrath [41], in their early study on entrainment, tested the effect of time limit on group performance and interaction. They found that altering the time limit had a significant effect on the group performance and interaction patterns and that the learned behaviors persisted in consecutive trials. The same authors in a later study altered the difficulty of problem solving tasks and found that the levels of effort that groups exert can also be entrained [42]. Libie et al. confirmed that social entrainment can be found in distributed groups, though they did not find significant differences between the way co-located and distributed groups changed over time [55]. All these examples seem to attest that the entrainment effect exists when the distribution of members are held constant.

When there is a change in distribution, however, there are mixed results about whether the previous behavior or the new condition is the stronger determining factor. Bos et al. observed partially distributed groups and switched the members who were distributed. They found that people who changed from being distributed to co-located adapted quite quickly to the co-located condition and formed new collaborative relationships, whereas people switched from being co-located to distributed had trouble, unsuccessfully trying to maintain their old ties with the once co-located members [12]. Hernes found that a change in communication medium is a stronger determinant than the existing structure of relationships. He found that the change in communication media easily altered the centrality of members and how members were perceived [34]. However, there is also support that the entrainment effect persists even when the distribution of members is changed. In a study of group identity, Bouas found that members who had been working in a dispersed team are likely to carry over their level of group identity even if they were assigned to a co-located group [14].

5.1.2 Social Dilemma Task and Change of Distribution

To observe the changes in performance, we chose to use the same Social Dilemma task used in 3.1. We found two examples of cooperation task studies that altered the geographical distribution of members. Rocco found that a face-to-face socialization meeting prior to a social dilemma task can promote the development of trust even when the actual task itself is done with members distributed [70]. They found that the group identity developed in the socialization round followed through even when they were later distributed. Wilson et al. repeated trials of a social dilemma task where the geographical condition is changed between rounds [83]. They found that groups that switched from distributed to co-located had an increase in cooperation level, and groups that were switched from co-located to distributed had a slight decrease in performance. Hence, the change in distribution seems to have a big impact on the group cooperation level.

To measure the effect of distribution, most of the prior work has only used the performance of the task as their dependent variable. A few exceptions exists where they also looked at the content of communication [55]. We proposed to observe non-linguistic communication patterns. We aim to verify the entrainment effect using sociometric data: if a style of communication pattern is entrained in a group, the group will try to keep their pattern even if the external conditions have changed.

5.2 Hypotheses

5.2.1 Groups Without Feedback

When a group is faced with the change in member distribution, we expect that there are two factors governing the post-change behavior of the group: (i) the tendency of groups to carry their pre-change pattern of behavior over to the post-change situation (social entrainment) and (ii) the adjustment (shift) of behavior caused in response to the change in member distribution.

We questioned whether the second factor disrupts the first factor, making groups drop their previously learned unique pattern of behavior. We hypothesize that when groups face change in distribution, the adjustments disrupts the learned behavior that groups need to learn a totally new style of behavior after the change. This will result in very little consistency between pre-change and post-change behavior of each group. Hence, knowing that a group is more talkative in the pre-change condition gives no power in predicting if this group would be talkative in the post-change condition.

To test the relationship between the pre-change and the post-change behaviors, we measure the correlation coefficient between the sociometric data. The correlation coefficient (R) will tell us how much the post-change behavior is dependent on the pre-change behavior. We are interested in understanding how much of the post-change behavior can be explained by the pre-change behavior (R^2). We are not looking at absolute values as there could be differences caused by the repeated nature of the study (e.g. all groups might talk less in the second round as they have already discussed their strategy before). We are looking at the behavior of a group compared to other groups in the same condition (e.g. if a group was more talkative than other groups in the first round, would the same group also be more talkative than other groups in the changed condition?).

> Pre-change behavior does not predict post-change behavior when groups face *change in distribution* (H5-a)

5.2.2 Groups With Feedback

In chapter 4, we found that sociometric feedback helped distributed groups behave more like co-located groups. This chapter applies the same sociometric feedback aiming to confirm its effect on change in member distribution. As we saw that the feedback reduced that effect of distribution in the cooperation task, we hypothesize it will also reduce the effect of *change in distribution*. The feedback will make the change in member distribution more subtle, eliminating the need to make adjustments, and therefore allowing us to see stronger consistency in behavior. We will see that once a group develops a unique pattern of behavior, this style of behavior will be found after the change as well, with the group showing similar behavior in the next round performing the same task. Therefore, if groups are performing the same task, they'll show similar behaviors despite the change of distribution.

> With feedback, pre-change behavior predicts post-change behavior when groups face *change in distribution* (H5-b)

5.3 Methods

5.3.1 Experimental Setup

To test the effect of feedback, we observed the data collected in section 3.1. The data has a control setting with no feedback and an experimental setting with group-level sociometric feedback. Each group participated in two rounds: once with all group members co-located in one room and once separated into pairs in two different rooms (Figure 5-1). Half of the groups started co-located and ended distributed (CO→DIS). For the other half of the groups, they had to participate in the first round separated into two rooms with no knowledge of who is in the other room and later moved into one room (DIS→CO). None of the groups were aware that their member distribution will change after the first round. In the previous chapter, we combined the two rounds' data into one data point. However, this chapter focuses on the comparison between the two rounds.

5.3.2 Participants

The data set includes 45 groups of four subjects each, total of 180 participants (99 male, 81 female, mean age=29.4, SD=10.0). Subjects were recruited on multiple university campuses and through Internet message boards. Due to equipment failure mentioned in section 4.2.2, one of the badges did not collect audio data in the first few experiments. Both badge and performance data was discarded for the feedback-condition sessions using this badge, as the feedback presented to the subjects was not accurate. However, the performance data of the

Performance and Survey analysis

	# of groups w/o Feedback	# of groups w/ Feedback
Co-located first	14	9
Distributed first	13	9

Sociometric Data Analysis

	# of groups w/o Feedback	# of groups w/ Feedback
Co-located first	8	9
Distributed first	8	9

Table 5.1: Number of four person groups included in the analysis.

no-feedback condition sessions were included in the analysis, as the decisions of the subjects were not affected by the badge malfunction. The total number of groups included in the analysis is shown in Table 5.1.

5.3.3 Tasks and procedures

All groups performed two rounds of the social dilemma task. After the first round, two of the subjects were asked to move. Special efforts were made so that the members in the DIS→CO group did not see the members in the other room before the study started. In each round, groups were given up to 8 minutes to discuss their strategy and come to a consensus. Based on Kelly et al.'s work, eight minutes is a sufficient length of time for groups to be entrained to a style of behavior which can be observed in following sessions [41]. Gersick even argues that lasting patterns can appear as early as the first few seconds of a group's life [29].

In both co-located and distributed settings, the earnings were dependent on the decisions of all four participants, requiring all participants to collaborate to maximize their group or individual earnings. All subjects received the average of their earnings in the two rounds. After each round, the total amount in the group fund was announced to all participants. Therefore in the second round, the subjects knew the total group fund amount of the first round, though they did not know the amount invested by each individual.

In previous studies, researchers have often conducted multiple, ten to thirty, trials to observe the temporal change in the group's cooperation level [70]. However due to the large number of trials and limited funding, each trial ended up with a very small amount of payoff which can easily reduce the motivation to make realistic decisions. As a tradeoff, we limited ourselves to two trials increasing the impact of each of their choice, so that a single decision could make up to a \$22 difference in their final payment. Even with this relatively high stake in decision-making, many of the participants mentioned that the amount was rather small to persuade them to deceive their group members, and stated that their decision might have been different if the amount was larger. Another reason we decided to limit our number of trials to two was the fact that initial phases of cooperation is when the biggest need for improvement exists. Bos et al. [13] found for advanced communication technologies, such as audio and video, the level of trust is low in the first few rounds but gradually reaches that of face-to-face as rounds are repeated.

5.3.4 Measures

Though many of our measures are individual based, we only used group level measures in the analysis as individual data points as members actions within a group is highly dependent on each other. Averaged values are used for the sociometric measurements listed in section 2.2.1: duration, body movement energy, variation in body movement, speaking time, balance speaking time, overlap speaking time, speech energy, speaking speed, and speech segment length.

Performance measures are identical to the ones used in section 3.1.2: level of cooperation and amount of defection. In both rounds, both the group's cooperation and defection can range from \$0 to \$64, which is the sum of all four members.

	w/o feedback		w/ feedback	
	CO→DIS	DIS→CO	CO→DIS	DIS→CO
Duration	0.09	0.08	0.88	0.28
Body Movement Energy	0.15	0.19	0.46	0.62
Var. in Body Movement	0.04	0.02	0.13	0.24
Speaking Time	0.27	0.02	0.66	0.49
Balance Speaking Time	0.03	0.01	0.12	0.05
Overlap Speaking Time	0.21	0.00	0.64	0.49
Speech Energy	0.28	0.00	0.59	0.48
Speaking Speed	0.26	0.05	0.62	0.06
Speech Segment Length	0.00	0.18	0.90	0.01
# of Turns/sec	0.02	0.01	0.58	0.02

Table 5.2: The consistency of pre-change and post-change behavior (R^2). Values listed are the amount of variance in the second round's data predicted by the first round's data. Colored cells are R^2 values with $p<.05$, N=(8, 8, 9, 9). Results show that there is no entrainment effect on communication patterns without feedback. However, feedback strengthens the entrainment.

5.4 Results

5.4.1 Groups Without Feedback

We compared the sociometric measurements of the first round (pre-change behavior) to that of the second round (post-change behavior). We did not find any correlations between the two rounds, i.e. social entrainment was not observed. We found no significant correlation in any of the sociometric measures (None of the r-values are significant in column 1 and 2 of Table 5.2). This result holds for both CO→DIS (column 1) and DIS→CO groups (column 2). Hence, we confirm our hypothesis: there was no trace of the pre-change pattern of behavior found in the post-change condition.

We use speaking speed as an example to interpret the results. In the initial round, each group developed their own style of behavior, some groups spoke faster, while other groups groups spoke slower. The correlation results show that the groups that spoke faster than other groups in the first round did not necessarily speak faster in the second round. In other words, observing the pre-change behavior did not predict the same group's post-change behavior. Hence, the behaviors developed in co-located settings do not carry over to when the groups are later distributed. And vice versa for the DIS→CO groups. Therefore we can understand that the contrast in the geographical condition is so apparent that the groups forget or drop their unique behaviors and develop a whole new style of behaviors when the member distribution change.

> Pre-change behavior does **not** predict post-change behavior when groups face *change in distribution* (H5-a)

5.4.2 Groups With Feedback

In groups without feedback, we found that the pre-change behavior had no predictive power over the post-change behavior (H5-a). However, when we give feedback, we find that the behavior of a group in the first round predicts how they are going to behave in the second round (Table 5.2: column 3 and 4). In column 3 and 4 of Table 5.2, we see statistically significant correlations between round 1 and round 2 in many of the sociometric features predicting 46% to 88% of the post-task variance (R^2). Again, to use speaking speed as an example, when provided feedback, groups that spoke faster than other groups in the first round also tended to speak faster in the second round. We saw in section 4.2.3 that the feedback, by reconstructing the functionality of social signals, reduced the gap between co-located and distributed conditions. The decreased gap between co-located and distributed settings seemed to have eliminated the need to adjust to the different conditions, making the transition between the two settings more subtle. The subtleness of the transition allowed groups in the second round to show their entrained behaviors from the earlier round.

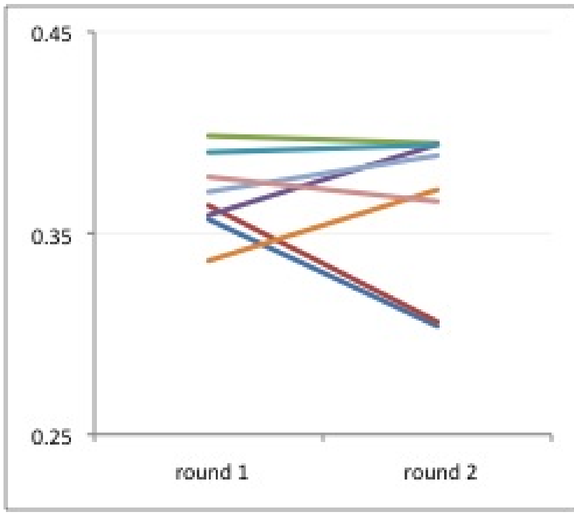
The consistency in behavior is observed in both CO→DIS groups (column 3) and DIS→CO groups (column 4). Comparing the two conditions, we see that the consistency is weaker for DIS→CO groups in a few measures when compared to CO→DIS groups. Almost all measures in the CO→DIS condition show a signficant correlation between round 1 and round 2 (Table 5.2, column 3) whereas only around half of the features show a significant correlation in the DIS→CO condtion (Table 5.2, column 4). McGrath speculated that one would find a similar phenomenon saying that a group's entrainment may be hindered in distributed settings due to the response lags and the loss of nonverbal cues [58]. Hence, we can posit that the level of entrainment in the initial round (within-trial effect) was weaker for groups that were distributed than the groups that were co-located, resulting in the across-trial effect being weaker in the second round. This result is in line with Bos et al.'s work, in which they found that DIS→CO groups had faster adjustment to their new setting, whereas the CO→DIS groups continued to keep signs of their old behavior.

We would like to note that this effect is not the result of feedback making all groups behave the same. In fact, often the variation among groups with feedback is often larger than that of groups without feedback (in the speech energy case, there is a 44% increase). What our results are showing is that the relationship between each group's first round behavior and second round behavior is quite strong, validating that each group's unique style of behavior persists even when there is a change of distribution. The feedback increased the consistency of the communication patterns in multiple dimensions.

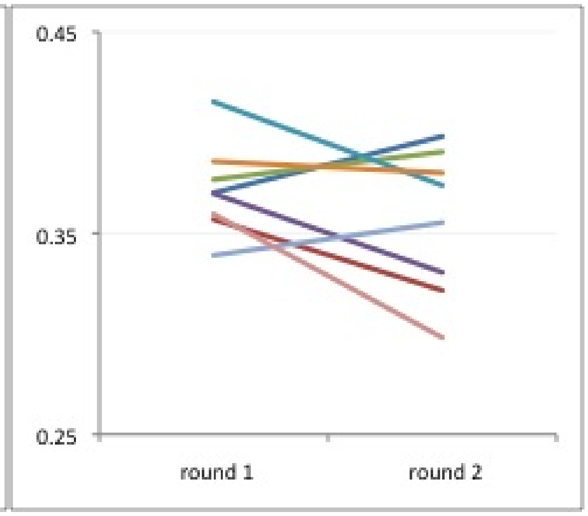
> With feedback, pre-change behavior predicts post-change behavior even when groups face *change in distribution* (H5-b)

Plotting the data makes this relationship more obvious. The body movement energy level of the pre-change and post-change conditions is visualized in Figure 5-2. As can be seen in Figure 5-2 (a) and (b), there is no consistent pattern between round 1 and round 2's body movement level when there is no feedback. However, when feedback is introduced, it is obvious from Figure 5-2 (c) and (d) that many of the lines are fairly parallel, showing that there is a consistency in how much a group moved in the first round with how much they moved in the second round. This relationship is confirmed in the correlation coefficients (r=0.68, p<.05 for CO→DIS and r=0.79, p<.05 for DIS→CO).

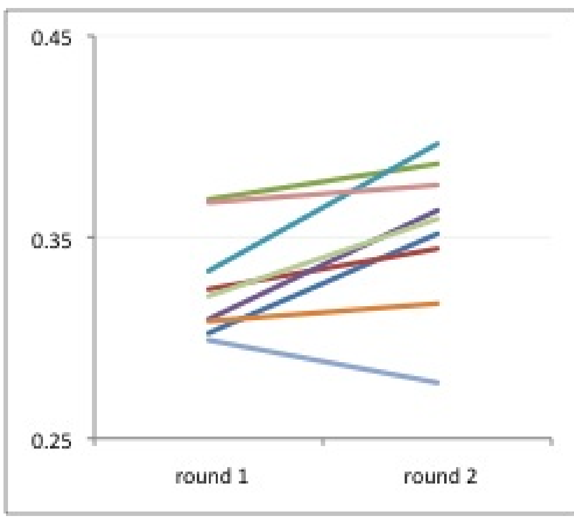
A meta analysis was conducted comparing the four different conditions using all ten communication patterns captured by the sociometric badge in Table 5.2. The mean R^2 values of the ten features measured by the sociometric badges were 0.14, 0.06, 0.56, and 0.27 for



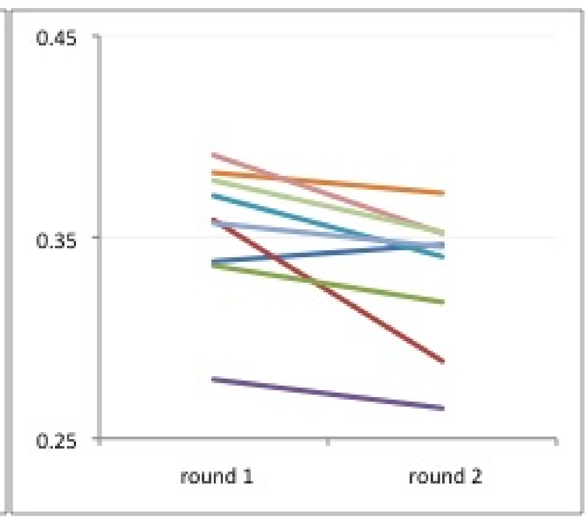
(a) CO→DIS without feedback (r=0.39, p=.34)



(b) DIS→CO without feedback (r=0.44, p=.27)



(c) CO→DIS with feedback (r=0.68, p<.05)



(d) DIS→CO with feedback (r=0.79, p<.05)

Figure 5-2: The pre-change and post-change body movement energy. Each line indicates a specific group, connecting their pre-change and post-change values. Without feedback there is no consistency in pre-change and post-change behavior, whereas the correlation is significant in the feedback condition.

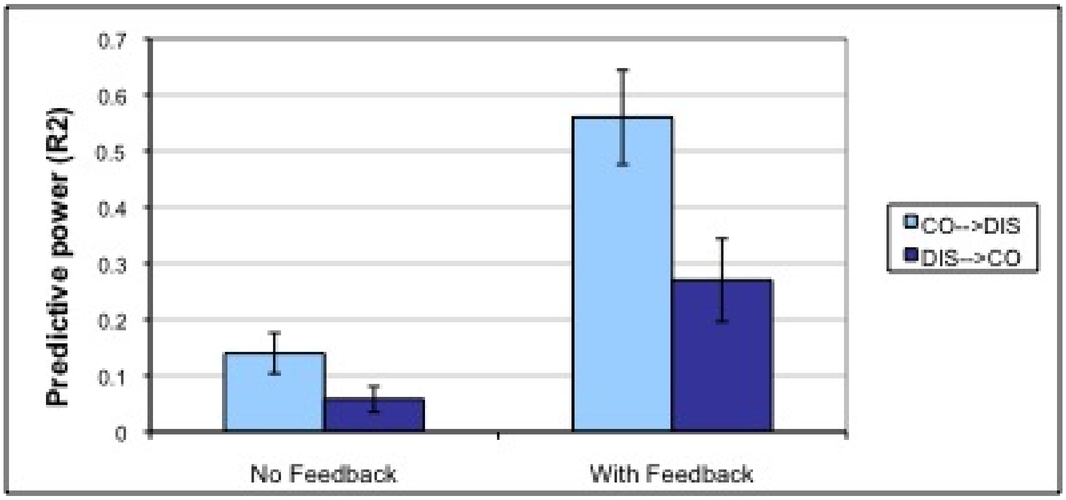


Figure 5-3: The meta analysis of the ten sociometric features (N=10,10,10,10). Feedback greatly increased the consistency between pre-change and post-change behavior, $F(1,36)=28.77$, $p<.05$. CO→DIS groups had stronger consistency than DIS→CO, $F(1,36)=9.25$, $p<.05$.

the four conditions (SD= 0.11, 0.07, 0.26, and 0.23, Figure 5-3). There was an extremely strong main effect for feedback ($F(1,36)=28.77$, $p<.05$) and change direction ($F(1,36)=9.25$, $p<.05$), and an interaction effect at the trend level ($F(1,36)=3.01$, $p=.09$). The sociometric data targeted only a few communication patterns, nonetheless the feedback increased the consistency of behavior in the multiple dimensions of data, surpassing what it initially targeted. Hence, supplementing a few of the social signals seemed to have changed the overall experience of the group, which is revealed through the various aspects of the sociometric data. This meta analysis strengthens our argument that the sociometric feedback increased the subtleness of the transition.

5.5 Discussion

Results show that when groups are faced with a change in member distribution, they are forced to make significant adjustment in their communication patterns. While the groups make this adjustment, they drop their previously developed behavior and develop a new pattern of behavior, which resulted in no correlations between the pre-change and post-

	w/o Feedback		w/ Feedback	
	CO→DIS	DIS→CO	CO→DIS	DIS→CO
Cooperation	\$58.3→\$53.1	\$50.2→\$43.0	\$52.1→\$54.4	\$59.7→\$55.2
Defection	\$2.0→\$10.9	\$9.8→\$21.1	\$1.2→\$9.6	\$4.3→\$8.9

Table 5.3: The average pre-change and post-change performance of groups. Groups without feedback tended to have lower cooperation rate in the second round than the first round. Feedback reversed this tendency so that the drop of performance is not significant even when the groups face change in member distribution.

change communication patterns. When real-time feedback is provided to groups, we see consistency in behavior before and after the change. As seen in chapter 4, feedback reduced the gap between distributed groups. This reduction weakened the impact of the change in member distribution, allowing groups to keep their unique pattern of behavior. Feedback helped distributed groups to learn patterns of behaviors similar to that of groups that are co-located, and let that entrained behaviors carry over even when there is a change in distribution, just as if the groups were continually co-located.

Now let's examine the performance of the groups. We find that the level of cooperation drops in the second round compared to the first round for most groups. This finding was mainly driven by two factors: (i) the fact that the subjects knew that the second round was the final round and (ii) the change in member distribution. Knowing that the second round was the final round, some of the subjects defected from their promises more than the first round as there would be no following consequences. In some cases, we saw some subjects intentionally cooperated in the first round in order to create trust only to earn more money on the second round through defection. However, when feedback is given, this drop in cooperation rate tended to be smaller than groups without feedback (the average drop was \$3.1 for group without feedback and \$0.6 for groups with feedback, $F(1,43)=2.3$, $p=.13$, Table 5.3, first row). It is interesting to mention that, when provided feedback, CO→DIS groups' cooperation actually increases (from \$52.1 to \$54.4) which is reversing the last-round-defection tendency.

The interpretation of the performance results is clearer as we examine the amount of defection (Table 5.3, second row). For groups without feedback there is a significant increase in defection for both CO→DIS and DIS→CO groups: increment of $8.1 for CO→DIS groups ($t(12)=-2.4$, $p<.05$) and an increment of $11.3 for DIS→CO groups ($t(13)=-2.8$, $p<.05$). However, for groups with feedback, the increment still exists but is no longer significant: increment of $8.4 for CO→DIS groups ($t(8)=-1.5$, $p=.17$) and an increment of $4.6 for DIS→CO groups ($t(8)=-1.9$, $p=.09$). Therefore groups tended to defect less when provided feedback. Hence, there seems to be factor that is reversing the last-round-defection tendency in the feedback conditions.

The confirmation of H5-b gives us a basis for understanding this phenomenon. The increased consistency in behavior between the two rounds may have helped groups to be more efficient and consistent as it eliminated the need to adjust their behavior [5, 33, 40]. The subtle transition made the groups communicate in a more similar pattern, helping them to feel like they are still in the same condition, thus making it harder for them to defect from their previous promises.

The limitations to our approach include the fact that our rounds were consecutive. Many of the prior work in social entrainment have had days or weeks in between studies which may have weakened the entrainment effect. Moreover, our experiment only included two rounds, thus not allowing us to learn the long term effects of entrainment. Our findings are also limited to a single task type. Hernes found that social entrainment is not observed when tasks change [34], a finding that we are curious to explore from the viewpoint of communication patterns and feedback. We leave many of our questions as future work.

5.6 Conclusion

We examined the consistency of behaviors in groups when there is change in their member distribution. We found that the change in member distribution is significantly disruptive that the groups tend to drop their previously trained behavior: there is no consistency between the pre-change behavior and post-change behavior. Sociometric feedback has a significant influence on this phenomenon. In the previous chapter, we have confirmed that sociometric feedback can make distributed collaboration more like co-located collaboration by reintroducing the functionality of lost social signals. Here we find that feedback also makes the *transition* between the two conditions more subtle. The sociometric feedback suppressed impact of the *change in distribution*, making groups behave as if they repeated the task in the same condition. This effect resulted in an improvement in performance.

With the advance of technology, we see more teams working remotely with their member distribution changing dynamically. This study offers insight into dynamically changing configurations of teams and its effect on performance and communication patterns. The effectiveness of the results indicate that feedback technology on group communication can reduce the effect of these changing conditions and strengthen entrainment which can lead to higher efficiency in teams.

Chapter 6

Conclusion

6.1 Generalization to Real-World Organizations

Our laboratory studies have verified that electronic sensors can effectively measure the interaction patterns of groups, identify successful patterns of communication, and influence the communication patterns and performance of groups. We explore the possibility of this research framework being applied to real-world teams. Results from two pilot studies conducted on real-world teams are reported.

6.1.1 US-Japanese Student Workshop

In collaboration with Ben Waber, Koji Ara, and Naoto Kanehira, the sociometric badges were deployed at a leadership forum held in Tokyo, Japan. The student participants wore the badges during all working hours for 7 working days. The forum involved an experiential group project of building a Rube Goldberg machine, which required creative engineering and the cooperation of all group members. The forum brought together 20 students from the US, mostly from universities in the Greater Boston area, and 20 students from Japan, mostly from universities in the Tokyo area. The 40 students were divided into 6 teams, each consisting of 6 to 8 students with the US and Japanese student number roughly matched.

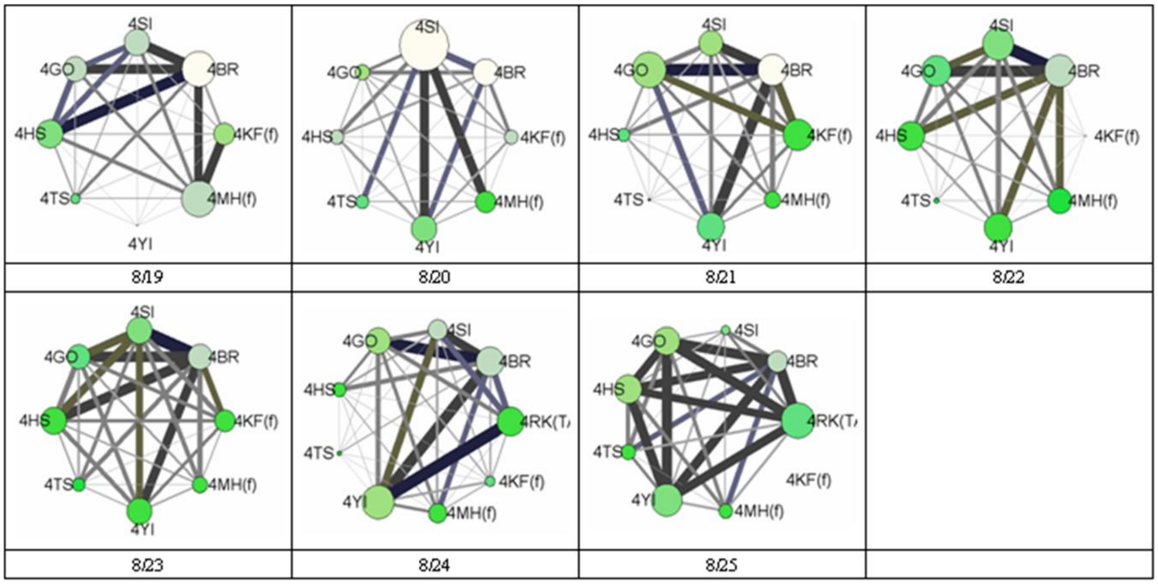


Figure 6-1: Evolution of a team's face-to-face interaction pattern over the course of one week

We observed their communication patterns as they were working together in teams. And at the end of each day, there was a reflection time, when each team got together and reflected on their day and made plans for the next day. At this time, we provided the team members with a sheet of paper including a visualization of the group communication patterns. The team facilitators were trained on how to interpret the data.

Figure 6-1 shows the sample visualization that a team received through out the week. It provides one of the team's face-to-face interaction pattern captured by the sociometric badges over the course of the week. The upper left diagram is the first day's communication pattern and the last day is the rightmost diagram in the lower row. The month and day of each diagram can be found underneath each visualization. The diagram is designed to encourage equal participation and higher interactivity, as the main task was to brainstorm creative ideas and methods to build a Rube Goldberg machine. Each circle in the diagram represents a member of that team, whose identity is represented by their initials next to the diagram. The size of each circle represents the amount of time a person participated in the conversation. The color of the circle represents how interactive each person was based on their turn-taking pattern (greener means more interactive), and the width of the edges represents the turn-taking patterns (thicker links indicate that the two connected nodes had a lot of back-and-forth conversations).

In this particular team, half of the students in the team were Japanese (4KF, 4MH, 4YI, 4TS) and the other half were American (4HS, 4GO, 4SI, 4BR). We can observe from the width of the links (turn-taking frequency) that the American students interacted mostly among themselves during the first few days and that this pattern changed over the course of the week, and the Japanese students became more integrated in the team. We can also see that one of the students (4SI) was taking the most dominant role on the second day but dramatically changes his behavior the next day. His change in behavior was probably due to the visual feedback he received after the second day. By the end of the week, the interaction pattern of the team became more balanced and highly interactive, which may be beneficial for collaborative idea generation.

We do not make any scientific conclusions from this experiment. Since all groups received the visualization of their communication pattern, we do not have a controlled condition to compare. Also the characteristics of the task changed (from more brainstorming to more hands-on building) as the time progressed, thus each day cannot be used as independent data points. Therefore, we cannot verify that our feedback caused this direction of change. However, this experiment verified that we can measure the communication patterns of real-world teams for long periods of time, and observe and analyze the temporal change in the data. Also informal interviews and survey results report that the participants found the visualization helpful on recognizing and mediating the gap between U.S. and Japanese students, which is supported by the sociometric data.

6.1.2 Bank Call Center

I introduce another example of a real world study where we saw clear value of sociometric feedback. Ben Waber, Daniel Olguin Olguin, Prof. Sandy Pentland, and I ran a two phase study at a call center of a major North American banking firm. During the first phase of the study, we targeted four teams at this call center, each consisting of around 20 employees.

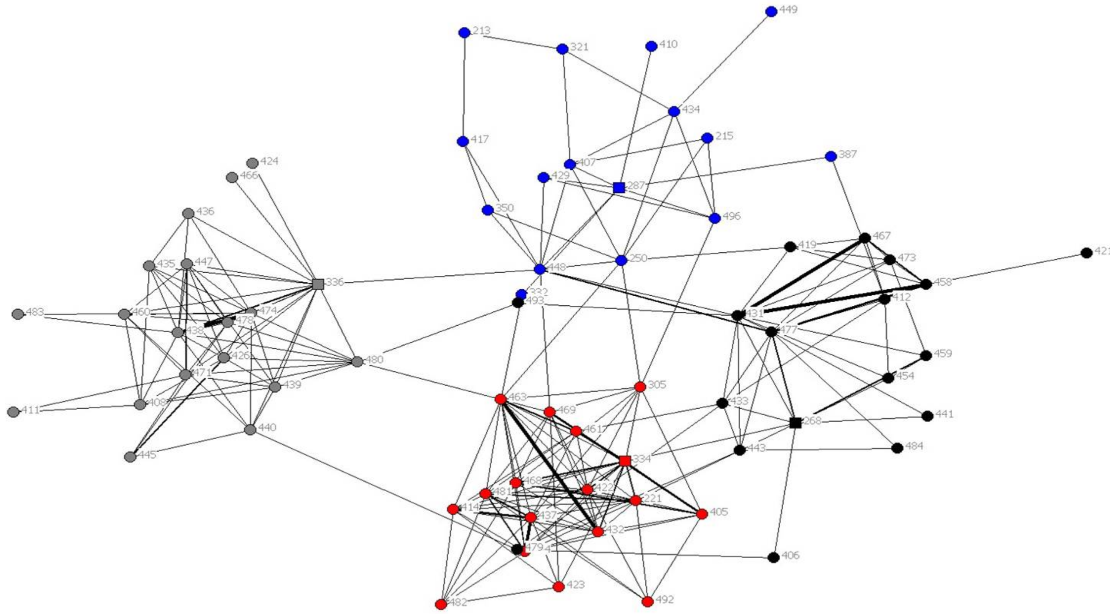


Figure 6-2: The pre-intervention social network diagram of four teams in a bank call center generated from their IR data. Employees are represented by circles of colors defined by their teams

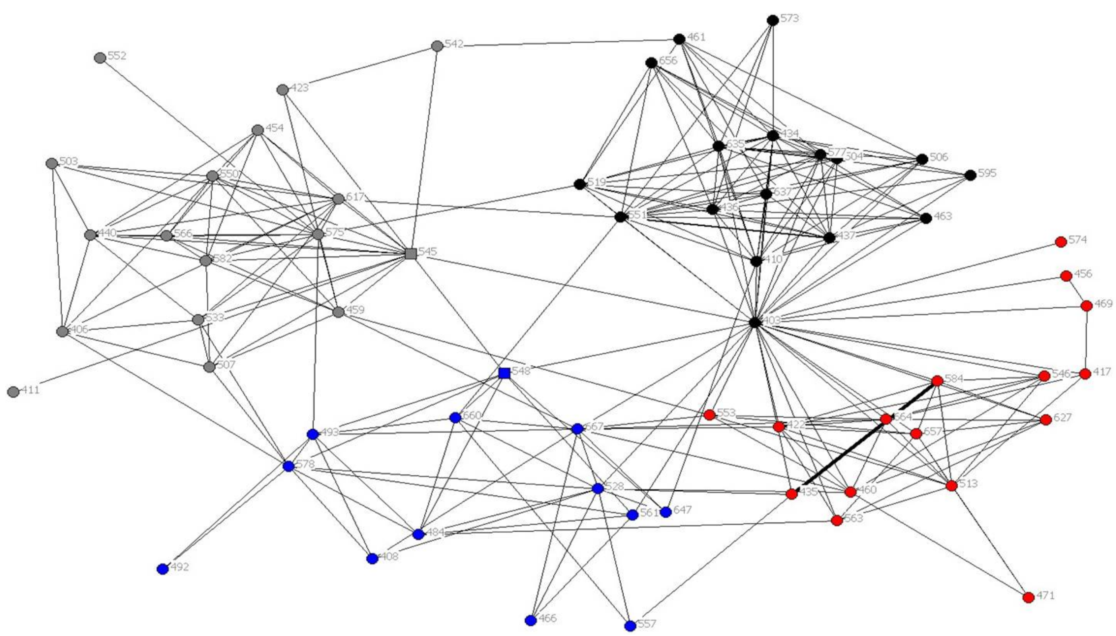


Figure 6-3: The post-intervention social network diagram of four teams in a bank call center generated from their IR data.

These employees were instructed to wear the Sociometric Badges all day while they were at the call center for a period of six weeks. The purpose of this phase of the study was to identify social behaviors that could lead to an intervention that would affect these behaviors and enhance productivity. In addition to the Sociometric Badges, we obtained productivity data from the call center. The measure of productivity provided by the bank is the average call handle time (AHT), which represents the cost of running a call center. The bank also gave the employees surveys as part of their regular monthly employee assessment, and we also were able to use this data in our analysis.

We visualized the social network using the IR data collected during the experiment (Figure 6-2). As we compare the data of the four different teams represented by four different colors, we see that the four teams seem to have a different style of behavior. For example, the red team on the bottom seems to have a tight social interaction pattern, in which all members seem to interact with all other members. On the other hand, the team in blue on top seems to have a very sparse interaction pattern. In this blue team, many of the members only have one or two connections. In this type of network structure, if a few of the most central people are missing, the communication would almost be totally disconnected. Hence, different teams seem to have a distinct style of communication, and we compare this pattern of communication to their performance.

Comparing the IR data with the performance, we see that the most productive employees are those who are embedded within the strongest social groups. The social embeddedness of an individual [31] was negatively correlated to average call handling time (AHT) for the employees that we studied ($r=-0.61$, $p<.001$). Our interviews and observations revealed that the frequent informal interaction among team members enabled fluid flow of information, which functioned as informal training. This sort of informal training was a critical factor to this call center as the average tenure of employees was only around 2 to 3 years. Hence, teams with strong social ties tended to have higher performance.

This result was rather surprising to the management of this call center. Originally, the structure of breaks of this call center, as in many call centers, was designed to minimize the interaction among the employees in an effort to minimize the wait time for the customers.

Each employee was given one 15-minute break per day in addition to a 30 minute lunch break, which would not overlap with any of their team members. This non-overlapping break structure was a legacy from the old days when there were a small number of call center employees, thus having overlapping breaks of multiple employees had a significant effect on the wait time for customers. However, now this particular organization has over 10,000 call center employees, so shifting call loads of a single group had almost no effect on the average call waiting time for customers. Not only does this strategy of non-overlapping break structure no longer help the average waiting time for customers, but our finding now points out that this strategy is actually hurting the performance of the employees by hindering informal training among team members.

Based on our finding, we worked with the call center to restructure the break schedules for the four teams that we observed. We changed the break structure so that all members in a team would breaks at the same time, encouraging interactions among the members. After giving this change three months to stabilize, we returned to the call center and measured the behavior of the employees again using the sociometric badges. We found that by giving employees breaks at the same time, we increased the strength of an individual's social groups (difference in mean strength of social group index was 0.19, a 23% increase, $p<0.05$). This change is seen in Figure 6-3, where you see that the overall connections among the members increased (especially those in the blue group). As we see the increase in the individual's social group strength, we expect that we will see an increase in performance. Unfortunately, we do not have access to the performance data of this second phase. However, the managers have expressed confidence that the new break structure has also enhanced performance. More detailed information can be found in [80].

6.2 Conclusion

This section reviews each component of the research framework introduced in section 1.1 (Figure 6-4). As discussed in Chapter 2, electronic sensors can be used to measure the interaction patterns of groups. The measured interaction patterns include non-linguistic speech

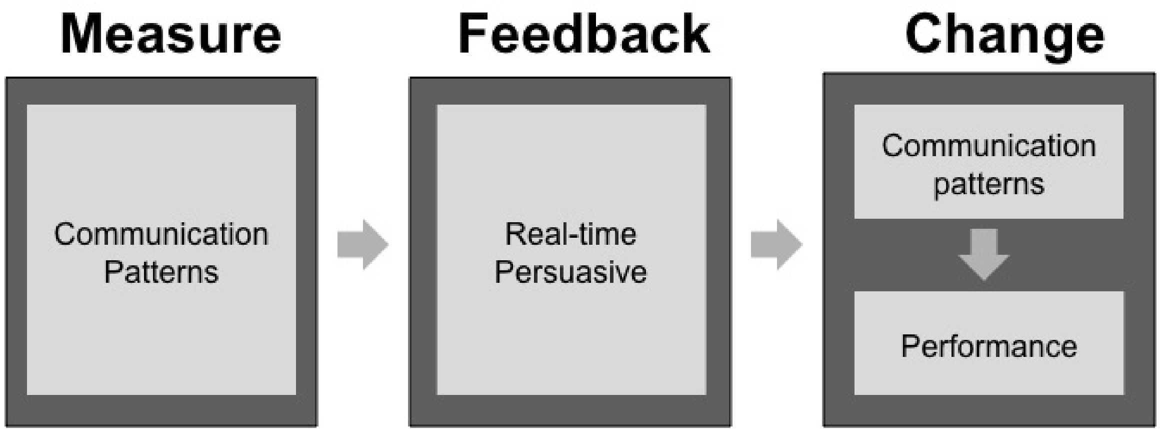


Figure 6-4: The research framework

features, movement features, and proximity features, which provides a description of the pattern the group is communicating. This quantitative measurement of social interactions is defined as "sociometric data". The sociometric badge measures the communication patterns of a wide variety of collaborative settings: both co-located and distributed meetings, as well as both short synchronous meetings and long-term dispersed encounters. This approach of measuring communication patterns opens the opportunity to measure objective, fine-level, longitudinal social interaction patterns of large number of people with very little cost.

Chapter 3 verified that the comparison of sociometric data with group performance can identify the patterns of communication, which lead to higher performance. Results of laboratory studies show that successful patterns of communication differ among tasks. For example, higher interactivity drove higher cooperation level of groups, while higher similarity in behaviors among the group members drove higher efficiency in their information sharing. However, for both tasks, the sociometric data had significant relationship with the group performance. This finding suggests that influencing communication patterns may improve the performance of groups.

The measured communication pattern was visualized on a mobile display as sociometric feedback in real time. Section 2.2.3 presented two examples of visualizations: a group-level feedback and an individual-level feedback. Norms defined by the task goal drove the design of these two examples: the group-level feedback was designed to encourage balance in participation and higher overall interactivity, while the individual-level feedback was designed to encourage lower centrality in turn transitions and higher interactivity of each participant. I intentionally designed the visualization as a persuasive interface to emphasize how much the group is deviating from the suggested norm. The visualization of sociometric data can and should be customized to the objective of the feedback, like the two examples shown in section 2.2.3. The main contribution of our experiments is not the comparison of various design methodologies of sociometric data, but instead proving that the visualization of a group's communication pattern can influence their performance.

Chapter 4 showed that the real-time visualization of sociometric data can improve the communication patterns and the performance of groups, and that this improvement was significant for distributed groups. For example, the sociometric feedback increased the interactivity level of distributed groups, which increased their cooperation level. The sociometric feedback also increased the similarity of behaviors among the group members, which increased their efficiency in information sharing. The study results confirmed our hypothesis that the feedback has a greater impact on distributed groups, making their communication patterns and performance more like co-located groups. The sociometric feedback seemed to have assisted distributed communication by providing an additional channel of communication.

Chapter 5 continues to report the effect of sociometric feedback. The chapter observed the effect of sociometric feedback on groups that face change in member distribution. Sociometric data showed that the change in member distribution forced groups to adjust their communication patterns, disrupting the consistency in their unique behavior. When sociometric feedback is provided, data reveal that groups continue to keep their learned pattern of communication despite the change in member distribution. Hence, sociometric feedback strengthened the consistency of pre-change and post-change behavior by making the transition between co-location and distribution more subtle, which had a positive influence on the group's cooperation level.

In agreement with our laboratory findings, Section 6.1 shows that sociometric measurements allow the identification of successful patterns of communication in real-world teams. Moreover, data proved that interventions based on sociometric data enhanced the communication patterns of workers, suggesting that it would lead to an improvement in performance. Most employees were fairly comfortable with wearing the badges during business hours, given that they were not recording the content of speech or taking pictures. Therefore, measuring the communication patterns of real-world teams and designing interventions based on the identified successful patterns hold great potential to enhance performance of real-world distributed teams.

I have presented a system that measures and visualizes the communication pattern of groups in real time. Laboratory studies using the system identified the relationship between communication patterns and performance, identifying behaviors that lead to higher performance. I utilized this learned relationship to influence distributed groups to change their communication patterns, which resulted in an improvement in their performance. Two pilot studies on real-world teams show potential for this system to have an impact on real-world organizations.

Previous chapters have shown that sociometric feedback can support rich interpersonal communication, making distributed groups communicate and perform no worse than co-located groups. I believe this work can be extended to have even greater value for groups. If we think far ahead, we can imagine that a well-designed sociometric feedback system may enable distributed groups to outperform co-located groups. This hypothesis is based on Walther's work, in which he argues that CMC could be extended so that it could facilitate communication that surpasses normal face-to-face interpersonal levels [81]. He refers this type of CMC interaction as *hyperpersonal* interaction. Given the ability to easily control and manipulate data, we may be able to explore opportunities to customize and modify sociometric feedback to overcome the problems that even co-located collaborations have. I believe sociometric measurement and feedback has potential to open doors to distributed collaboration surpassing the communication and performance of co-located teams.

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