

Understanding the Link Between Changes in Social Support and Changes in Outcomes with the Sociometric Badge

by

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M.A., Boston University (2002)

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Submitted to the Program in Media Arts and Sciences,
School of Architecture and Planning,
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Abstract

The goal of this thesis is to show that social support created through face-to-face interaction is a driving factor in a number of important outcomes. Through a series of studies we show that social support, operationalized using face-to-face network constraint (information clearing), is positively related to important outcomes such as productivity and job satisfaction and that changes in social support are positively related to changes in these outcomes. We then discuss a two-phase study where we experimentally modify break structure to increase network constraint and demonstrate a corresponding positive change in outcomes. Finally, we show that network constraint is also qualitatively related to outcomes and is an effective proxy for social support. To conclude we situate this research under a larger framework that provides direction for future research.

Thesis Supervisor: Prof. Alex (Sandy) Pentland
Title: Toshiba Professor of Media Arts and Sciences

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Chapter 1

Introduction

There has been strengthening of forces pushing organizations to rely more heavily on remote collaboration (Jarvenpaa and Leidner 1999). Pressures that range from a workforce that demands flexibility to large projects that span multiple continents make the arguments for expanding and embracing remote work very compelling. Face-to-face interaction is increasingly being replaced by electronic communication, but many are worried that effective communication patterns that occur in a co-located setting do not naturally transfer to the distributed workplace.

There are some behaviors that currently cannot be replicated by a purely technological solution. Serendipitous interaction, a key driver of innovation within corporations (Nonaka 1998), relies on physical layouts and social cues to function correctly. Breaks function similarly, and part of their utility is that they allow employees time to trade tips and to commiserate. Beyond these isolated events there is the question of how overall communication patterns, rather than isolated events, drive employee effectiveness and satisfaction.

The positive effect of strong social embeddedness in face-to-face networks on outcomes has been documented in many different settings, as outlined in (Reagans and Zuckerman 2001). The problem with much of this research is that the results are correlational, which makes it difficult to attribute causality. In this thesis we take this problem head on. In particular, we will:

1. Show that social embeddedness is positively related to important outcomes.
2. Show that changes in social embeddedness is positively related to changes in outcomes.
3. Change break structure to increase social support and demonstrate a corresponding positive change in outcomes.

4. Show that social support is also qualitatively related to outcomes

1.1. Collecting Data

It has been difficult to collect behavioral data on face-to-face interactions, and most social science research makes use of surveys to collect this information. Since researchers are often aware of the substantial limitations of the survey approach - subjectivity, inaccuracy, limited scope - human observation and interviews have been employed to supplement survey data (Mergel, Lazer and Binz-Scharf 2008). Unfortunately, observation and interviews can be imprecise and do not scale well when one wishes to study hundreds of people across dozens of sites.

Wearable sensing technology, however, has now advanced to the point where researchers can use sensors that collect direct micro-level data on face-to-face interactions to ask and answer previously intractable research questions (Lazer, et al. 2009). In this thesis, will introduce and discuss a new set of research tools and methodologies collectively known as *Sociometric Badges* – wearable sensing devices designed to collect data on face-to-face communication and interaction in real time.

To highlight opportunities and challenges for management research, in this thesis we will also discuss a) potential opportunities for information systems (IS) and management research, b) key trade-offs, challenges and research design choices, and c) important limitations of the tools and techniques. We believe this set of technologies, which will soon be publicly available for research purposes at low cost, will enable management researchers to explore new research questions and more accurately address existing lines of research.

Recently, electronically recorded data on communications and behaviors have been proposed as a solution to overcome the limitations of the survey approach (e.g. (Aral, Brynjolfsson and Van Alstyne 2006); (Aral, Muchnik and Sundararajan 2009); (Aral and Van Alstyne 2010)). Not only are data sources such as e-mail, Instant Messaging (IM), and computer use widespread, but data from these types of electronic systems are also easily accessible and provide a wealth of information orders of magnitude more precise than survey data (Quintane and Kleinbaum 2008); (Huang, et al. 2009). Mining social network data from e-mail traffic and obtaining detailed task information from online code repositories have expanded opportunities for research (Howison and Crowston 2004). Yet surveys remain the most popular assessment method. The reason is simple: some of the most important behaviors still take place offline. People rarely sign billion dollar merger deals without meeting face-to-face to negotiate. Until now, surveys were the only viable means of measuring non-electronic communication and behavior. But questions have persisted about the validity of survey research for accurately capturing behavior (Marsden 1990).

Sensors offer an opportunity to bridge the gap between purely survey-based methods and data that only capture computer-mediated behavior. Sensing technology, from devices as complex as cell phones to those as simple as a Radio Frequency Identification (RFID) card, have become ubiquitous in the modern organization. While these devices are primarily viewed as tools to help people communicate or get around a building, they are also capable of generating huge, detailed datasets about real world activity at an unprecedented scale (Lazer, et al. 2009).

Current sensor platforms, however, still do not capture all of the data that organizational researchers, and social scientists in general, are interested in. Cell phones are typically kept in a pocket and so make it difficult to observe face-to-face interactions. RFID cards are passive and

cannot capture any data beyond proximity to environmentally embedded RFID readers. Pentland envisioned a device that could accurately and continuously track the behavior of hundreds of humans at the same time, recording even the finest grained behaviors with great accuracy (Pentland 2006). Our research group has identified six important capabilities that a robust wearable sensing platform of this type should possess: 1) detection of human movement, 2) recording of speech features (rather than raw audio), 3) wireless data transfer capabilities, 4) indoor localization, 5) detection of proximity to other individuals, and 6) detection of face-to-face interaction.

To satisfy all of these requirements the Human Dynamics group at the MIT Media Lab created the *Sociometric Badge* (Olguin Olguin, Waber, et al. 2009), a comprehensive wearable sensing platform designed to automatically capture individual and collective patterns of behavior. In Section 7.2 we build a research framework to suggest new avenues for research that this technology enables.

Chapter 2

Background

2.1. Sociometric Badges

The advent of low cost, flexible sensing systems has enabled us to more accurately quantify face-to-face interactions, particularly in the workplace. Many employees in larger companies are required to wear RFID name tags that allow them to open doors or access other resources, although this data is rarely harnessed so people can understand how individuals are actually moving around the workplace. In addition, it is possible to augment these name tags with additional sensors to understand in more detail how people interact with each other and even fiddle at their desks. This leap forward in technology allows us to re-examine some previous research on social networks using behavioral data as well as examine changes in face-to-face communication activity in much greater detail.

This technology has the potential to fundamentally alter the types of questions that we ask. This data is naturally more precise, allowing us to study, for example, behavioral data on the order of five-minute chunks related to specific tasks automatically logged by an IT services firm (Waber and Pentland 2009).

The Sociometric Badges are useful for researchers to get a realistic picture of what kinds of communication is actually driving productivity in the workplace. In survey responses people often cannot accurately differentiate between communication media that they used to communicate with another person. Without behavioral data, it is difficult to be confident in the validity of the communication data that is obtained.

Communication patterns also change quickly. Project phases can last only a few days and entire teams can come together and dissolve in less than a few months. By analogy to the Nyquist rate in signal processing, to adequately sample behaviors they have to be sampled at least twice their rate of change to be accurately reconstructed. Therefore collecting communication data at fine levels of granularity is critical to studying and understanding these phenomena.

We have created a wearable Sociometric Badge that has advanced sensing, processing, and feedback capabilities (Olguin Olguin, Waber, et al. 2009). In particular, the badge is capable of:

- Recognizing common daily human activities (such as sitting, standing, walking, and running) in real time using a 3-axis accelerometer (Olguin Olguin and Pentland 2006).
- Extracting speech features in real time to capture nonlinguistic social signals such as interest and excitement, the amount of influence each person has on another in a social interaction, and unconscious back-and-forth interjections, while ignoring the words themselves to assuage privacy concerns (Pentland 2005).
- Performing indoor user localization by measuring received signal strength and using triangulation algorithms that can achieve position estimation errors as low as 1.5 meters, which also allows for detection of people in close physical proximity (Sugano, et al. 2006).
- Communicating with Bluetooth enabled cell phones, PDAs, and other devices to study user behavior and detect people in close proximity (Eagle and Pentland 2006).

- Capturing face-to-face interaction time using an infra-red (IR) sensor that can detect when two people wearing badges are facing each other within a 30°-cone and one meter distance.



Figure 1. Sociometric Badge.

Detecting Face-to-Face Interactions

IR transponders, which transmit directed beams of infra-red light, can be used as a proxy for the detection of face-to-face interaction between people. In order for one badge to be detected through IR, two Sociometric Badges must have a direct line of sight to each other. The receiving badge's IR sensor must be within the transmitting badge's IR signal cone of height less than one meter and radius r such that:

$$r \leq h \tan \theta, s. t. \theta = \pm 15$$

Figure 2 shows a receiving badge's IR sensor within the specified range. Every time an IR signal is detected by a badge we say that face-to-face interaction may occur.

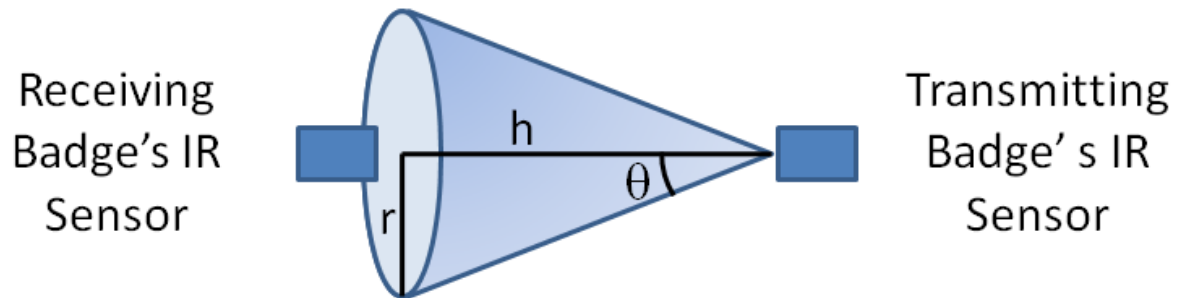


Figure 2. IR Transmission Diagram. Face-to-face interaction is detected when the receiving badge's IR sensor is within the transmitting badge's IR signal cone.

The Sociometric Badge will fail to detect interactions when people are not oriented towards each other when having a discussion. If an obstacle is blocking the IR transmission between the two badges interactions will similarly not be detected. While this is a concern, Choudhury and Pentland (Choudhury and Pentland 2003) showed this form of IR sensor detects approximately 87% of face-to-face interactions, assuring us that we will capture the vast majority of interactions that occur. We define the total amount of face-to-face interaction time per person as the total number of consecutive IR detections per person multiplied by the IR transmission rate, which in our experiments was once every two seconds.

Measuring Physical Proximity and Location Using Bluetooth

Sociometric Badges can detect other Bluetooth devices in close proximity in an omnidirectional fashion (within a 10 meter radius). In the past, this functionality has been used to identify location, behavioral patterns, and social ties (Eagle and Pentland 2006). It is possible to determine approximate location from base stations and other mobile badges using Bluetooth technology. If a person is detected within the Bluetooth transceiver's range, it does not necessarily mean that they are interacting with each other. However we can ascertain that they are in close proximity to each other, easily reachable for face-to-face interaction.

Initially we hypothesized that Bluetooth detections could be used to recognize office level locations and conversational groups. However the large range of the Bluetooth receivers made this task extremely difficult, limiting the resolution of our data. This led us to take a different approach to the analysis. Since closer devices are detected more often, we say that two people are in close proximity to each other only if their Bluetooth IDs are detected for more than 15 minutes during one hour. In our experiments, each badge was detectable over Bluetooth every ten seconds, and each badge performed a Bluetooth scan every five seconds. This accounts for the limited Bluetooth detection rate.

Detecting Physical Activity Levels

The badge's 3-axis accelerometer signal is sampled at $f_s = 250 \text{ Hz}$, which should be able to capture the range of human movement and could be as low as 30 Hz since 99% of the acceleration power during daily human activities is contained below 15 Hz (Mathie, et al. 2004). The range of values for the accelerometer signal varies between $-3g$ and $+3g$, where $g = 9.81 \text{ m/s}^2$ is gravitational acceleration. To normalize the signals, a calibration procedure is necessary to obtain the absolute value of gravity and the zero gravity point g_0 . To obtain these values we slowly rotated one badge in all directions.

The accelerometer samples recorded from each badge a_i are normalized as follows:

$$a_i^* = \frac{a_i - g_0}{|g|}$$

The acceleration Signal Vector Magnitude (SVM) provides a measure of the degree of movement intensity that includes the effect of signal variations in the three axes of acceleration (Karantonis, et al. 2006). The SVM is calculated on the normalized i^{th} acceleration sample as follows:

$$SVM_i = |a_i^*| = \sqrt{a_{x_i}^{*2} + a_{y_i}^{*2} + a_{z_i}^{*2}}$$

To distinguish between periods of activity and rest the average SVM is calculated over one-minute segments:

$$SVM(k) = \frac{1}{f_s T} \sum_{i=1+f_s T(k-1)}^{f_s T k} SVM_i$$

where $T = 60$ is the time segment (in seconds) over which the average SVM is calculated, and $k = 1 \dots K$ is the number of minutes a person was wearing the badge during the day. When the badge is not being worn $SVM(k) \leq 1$, since only the component of gravitational acceleration is detectable. Individual daily activity level is defined as the average $SVM(k)$ score over the entire day, and we define *average energy* as the average $SVM(k)$ score over a specific period of time. The *standard deviation of energy* is similarly the standard deviation of $SVM(k)$ over a specific period of time.

Detecting Speech and Conversations

Objective social signaling measures based on non-linguistic vocal attributes to determine social context have been developed within our research group (Pentland 2005). We take a similar approach to characterize the interaction between individuals and determine the percentage of time that an individual is engaged in a conversation. By examining the variation in pitch and volume in the audio signal, we are able to distinguish speaking from non-speaking signals (Koyrakh, Waber, Olguin Olguin, & Pentland, 2008).

We are also able to detect conversations by using the mutual information (MI) between the speaking and non-speaking signals of many subjects (Koyrakh, et al. 2008). By using proximity information derived from our Bluetooth and 2.4 GHz radios, we are also able to

distinguish between phone conversations and face-to-face interactions, although in our analysis we ignore phone conversations because of the scarcity of this kind of data.

E-mail Analysis

E-mail has been frequently used to measure social ties between individuals (Aral, Brynjolfsson and Van Alstyne 2006). In workplaces today employees are interacting with each other more and more frequently through e-mail as well as other electronic communication channels, and between 1996 and 2006 employees at a large technology company received on average 78% more e-mails a day (Fisher, et al. 2006). This data is easily quantifiable, since we know exactly who sent an e-mail to whom and when. Because e-mail only captures digital interactions, it is unclear whether this accurately represents “real” interactions versus information broadcast. In general, large scale unidirectional e-mails have little value when analyzing one-on-one interaction as it is unclear if information has actually been transferred without a response. Therefore we only consider reciprocated e-mails when examining communication between individuals as in previous work (Bird, et al. 2006).

Relational Data Analysis

Relational data (i.e. IR detections, e-mail exchanges, Bluetooth proximity) must be placed into an adjacency matrix in order to analyze it under a social network framework. In relational data there are two participants: a sender i and a receiver j . We define the matrix A with elements a_{ij} such that:

$$a_{ij} = \max(a_{ij}, a_{ji})$$

where a_{ij} is the amount of communication measured between i and j . This procedure creates a symmetric matrix and a social network representation.

The betweenness of a node o in a social network is defined as the proportion of all shortest paths between any two nodes in the network that pass through o (Scott 2006).

Mathematically, we have:

$$b_o = \sum_{o \neq v \neq t \forall v, t \in V} \frac{\alpha_{vt}(o)}{\sum_{i \neq v \neq t \forall i \in V} \alpha_{vt}(i)}$$

where α_{vt} is the number of unique paths in the social network from node v to node t that pass through o and b_o is the betweenness of o .

We define the network constraint c_i of a node i in a social network as the degree to which an individual's contacts are also connected to each other, and the calculation is identical to that proposed by Burt (Burt 1992) for network constraint. P_{ij} is the proportion of i 's time invested in communicating to j . The equation is as follows:

$$c_i = \sum_j (p_{ij} + \sum_q p_{iq} p_{qj})^2, q \neq i, j$$

The contribution index has also been found in the past on IR sensor data to be strongly positively correlated with extraversion (Fischbach, Schoder and Gloor 2009). This is defined by the equation:

$$\frac{(\text{IR Messages Transmitted} - \text{IR Messages Received})}{(\text{IR Messages Transmitted} + \text{IR Messages Received})}$$

This equation takes advantage of the directional nature of IR transmissions, capturing how much people are facing each other during a conversation. Thus, if an individual has a contribution index of 1, they always face the people they talk to, while if a person has a contribution index of -1, they never face others when they are having a discussion. We include this in our analysis below to control for personality variance as well as potential change in badge usage across the study.

2.2. Social Networks

Social networks have become an active area of research in the social sciences, describing the pattern of relationships that connect individuals together. Under the social network framework, patterns of relationships or communication are represented as a graph, with nodes representing individuals and edges, or ties, representing a relationship or communication event between two people. Using this framework, it is possible to study not only the raw volume of communication that an individual is engaged in, but also the structure of that communication. For instance, is an individual communicating with people who don't speak much to each other, or are they embedded within a dense set of links where all of their contacts speak to each other?

One can also ask about a person's global position: how central is a particular person to the whole social network? While there are many ways of measuring this quantity, the most commonly used metric is betweenness centrality (Scott 2006). Conceptually, betweenness centrality captures how many shortest paths in the network between two people go through an individual. High betweenness is often termed an "information advantage," where information that travels from person to person is more likely to be received by an individual with high betweenness before someone with a more peripheral network position (Aral, Brynjolfsson and Van Alstyne 2006).

Complementary to the idea of betweenness is the concept of structural holes (Burt 1992). This is more of a local measure of importance than betweenness, essentially capturing to what degree people are in advantageous positions by connecting groups of people who don't have ties to each other. The perceived advantage of structural holes is that an individual in this position can exploit information asymmetries across different groups. An individual that occupies a

network position with many structural holes can also “close the loop” between different groups by introducing them, potentially receiving accolades in the form of increased income or respect. Individuals that occupy a position with a number of structural holes are sometimes termed to be in a “bridging” position, emphasizing their role as a spanner of multiple groups.

It is easy to see why being in a bridging position could be advantageous with regards to information gathering. If you are looking for a job, you will have a better chance of finding one if your friends are spread out across many different companies than if they are concentrated in a few. If you’re trying to get a sense of a community’s reaction to a new policy, it’s better if you know people in diverse social groups. People in a bridging position could exploit this information for power, for example by preventing communication between two groups unless certain conditions are met.

Research has largely confirmed these advantages. Centrality has been linked to higher performance (Reagans and Zuckerman 2001), faster receipt of new information (Aral, Brynjolfsson and Van Alstyne 2006), and power (Ibarra 1993). In some of this research, social support, operationalized as network density or so-called network constraint, is associated with lower performance.

As a result of this work, some researchers have praised organizational processes that promote structural holes (Walsh and Maloney 2002). Many recent organizational innovations directly or indirectly impact the formation of structural holes. E-mail communication allows geographically dispersed people to communicate. The rising prevalence of telecommuting creates a preponderance of disconnected groups.

Less often explored are the potential downsides of being in a bridging position. Compared with people who are embedded in a dense network of ties, central people will not be

as much a part of a single community. By definition they are connecting different groups of people together, and so they may have to navigate different norms and relationships. Meta-analysis of the literature has shown that this manifests itself in terms of lower job satisfaction (Brown and Peterson 1993).

The potential advantages of structural holes often conflict with these drawbacks in the literature and the potential advantages of ties embedded within strong cliques (fully connected groups of people within a social network) called Simmelian ties (Krackhardt 1999). These ties are likely to emerge in teams where continuous and intensive communication is required between team members. People in these cliques will often have similar norms as well as higher levels of trust, and in face-to-face communication networks these ties have been linked to higher performance (Wu, Waber, et al. 2008). This contrasts with the information advantage perspective that Simmelian ties should not be effective since they do not bring additional unique information.

Simmelian ties deal explicitly with relationships that are of equal weight. When relationships have different levels of importance, network constraint (information clearing) is used (Burt 1992). Network constraint measures the degree to which ego's alters are connected to each other and how much of their time is spent speaking with each other rather than with people ego does not communicate with. Networks high in constraint have been shown to exhibit more social support (Granovetter 2005); (Reagans and McEvily 2003).

The negative connotations of the term "constraint" concern us. This implication may come from the fact that across all contacts in our lives, having a constrained network would be ineffective at hearing about job opportunities or other new pieces of information. Since we are examining networks within organizations, however, networks high in "constraint" would not be

very constraining since people are privy to similar sources of information. Instead, in the organizational context a network high in constraint would be more effective at information clearing (checking information and having in-depth discussions with peers). In Section 7.3 we delve into this topic and suggest that within organizations different terminology could be employed.

Increasing network constraint does not necessarily mean communicating with more people. If you and the people you already communicate with begin talking to another person frequently, then that will increase everyone's constraint. Adding a number of communication partners who do not speak with anyone else you speak with, on the other hand, will reduce your network constraint. In the methods section we will present the precise equation for calculating network constraint. From an individual perspective, then, there is a tension between growing your network and maintaining a high level of communication between all of your contacts.

Structural Holes vs. Network Constraint

As we have seen, there is often a tension between the entrepreneurial advantages of structural holes, which have been linked to higher performance (Reagans and Zuckerman 2001), versus the supportive nature of Simmelian ties and networks high in constraint (information clearing). It has even been pointed out that many of the conflicting results on this front may be due to the lack of a standard measurement mechanism (Flap and Volker 2001), and we believe that the Sociometric Badges and human behavior sensing technology in general will help rectify this situation by acting as consistent data sources.

Krackhardt's theory on Simmelian ties (Krackhardt 1999) attempts to disambiguate this debate by placing the context of the type of network examined in the center. The theory states that in certain circumstances being in a bridging position can be more constraining than being in

a non-bridging position since one's behaviors have to conform to the norms of multiple groups rather than one. This is in contrast to Burt's structural holes theory which focuses on the information advantage enjoyed by bridging individuals (Burt 1992).

Krackhardt clarifies the mutual compatibility of these views by asserting that when people have to express themselves publicly, bridging positions will be more constraining on one's behavior. In this case you will publicly have to align yourself with norms from different groups. When people are able to communicate more in private, Burt's theory would apply.

These public and private constraints can be enhanced or reduced by different communication media. Face-to-face communication, for example, is in some cases a public forum since it can be observed by anyone walking by. E-mail, in contrast, can be explicitly directed to one person and so may be considered private. By examining the above arguments through the lens of media richness theory, we may gain additional insight into the apparent contradiction between embeddedness and bridging.

Media Richness and Social Networks

Media richness theory was introduced by Daft and Lengel (1986). Here media richness is defined as the ability of information to change understanding within a time interval. Face-to-face interaction under this rubric would have the highest richness, while e-mail due to its asynchronicity and purely textual representation would be lower. Communication media such as video conferencing and instant messaging sit between e-mail and face-to-face communication since while they are synchronous technological limitations in resolution and time lag introduce difficulties in these interactions. While in our studies we only examine face-to-face and e-mail communication, we believe that our results have implications for these other forms of communication.

Different types of communication media are optimal in different circumstances. In addition, Daft and Lengel point out that the structure of communication in different circumstances will also change. Figure 3 reproduces their figure on technology (knowledge, tools, and techniques used within an organization) viewed on the axes of analyzability and variety. Analyzability indicates the degree to which a technology can be understood or utilized by an employee with an objective, computational procedure (Daft and Lengel 1986).

ANALYZABILITY	Unanalyzable	<p>1. Unanalyzable, Low Variety (Craft Technology)</p> <p><u>Structure</u></p> <p>a. Rich media to resolve unanalyzable issues</p> <p>b. Small amount of information</p> <p><u>Examples:</u> Occasional face-to face and scheduled meetings, planning, telephone</p>	<p>2. Unanalyzable, High Variety (Nonroutine Technology)</p> <p><u>Structure</u></p> <p>a. Rich media to resolve unanalyzable issues</p> <p>b. Large amount of information to handle exceptions</p> <p><u>Examples:</u> Frequent face-to face and group meetings, unscheduled meetings, special studies and reports</p>
	Analyzable	<p>3. Analyzable, Low Variety (Routine Technology)</p> <p><u>Structure</u></p> <p>a. Media of low richness</p> <p>b. Small amount of information</p> <p><u>Examples:</u> Rules, standard procedures, standard information system reports, memos, bulletins</p>	<p>4. Analyzable, High Variety (Engineering Technology)</p> <p><u>Structure</u></p> <p>a. Media of low richness</p> <p>b. Large amount of information to handle frequent exceptions</p> <p><u>Examples:</u> Quantitative data bases, plans, schedules, statistical reports, a few meetings</p>
	Low	High	
	VARIETY		

Figure 3. Analyzability and Variety of Technology. From (Daft and Lengel 1986).

The examples of communication behaviors listed in each box clearly suggest different effective network structures in specific communication media. Difficult to analyze technology needs rich media (face-to-face) as well as a densely connected group of people around the problem to deal with unforeseen circumstances. Face-to-face interaction also enables but does

not guarantee the development of trust and a common vocabulary, which is necessary to transmit complex information (Huang, Gattiker and Schwarz 2008). More codifiable situations, however, can be more quickly dealt with through the use of media with low richness (e-mail). In these situations it is more helpful to be connected to a diverse group of other people since a wide variety of information is preferable once questions of common vocabulary are removed, and therefore high e-mail betweenness would be the most effective network structure. These categorizations are also supported by (Sheer and Chen 2004), who show that complex tasks were discussed more through face-to-face communication.

In Figure 4 we show the original table with the appropriate network structures and communication medium inserted.

ANALYZABILITY	Unanalyzable	1. Unanalyzable, Low Variety (Craft Technology) <u>Network Structure:</u> Moderate Network Constraint	2. Unanalyzable, High Variety (Nonroutine Technology) <u>Network Structure:</u> High Network Constraint
	Analyzable	3. Analyzable, Low Variety (Routine Technology) <u>Network Structure:</u> High e-mail betweenness	4. Analyzable, High Variety (Engineering Technology) <u>Network Structure:</u> Low e-mail betweenness
		Low	High

VARIETY

Figure 4. Analyzability and Variety of Technology With Appropriate Network Structures.

In organizations where employees are engaged in knowledge work, a large amount of their communication is devoted to discussing knowledge, tools, and techniques. Therefore media richness theory posits that if people do not structure their communication patterns as

suggested above, then they would have increased uncertainty and ambiguity about their role within the organization, as well as lower performance (Daft and Lengel 1986).

To summarize, people with high network constraint have been shown to engender higher levels of social support, particularly in face-to-face networks, which increases job satisfaction and productivity. Media richness theory argues that these networks would have the additional benefit of reducing role conflict and ambiguity and subsequently increase job satisfaction, indicating that this would add to the positive effect of face-to-face network constraint.

Hypothesis 1: Higher face-to-face network constraint implies higher productivity.

We now present our first study to answer this question.

Chapter 3

Chicago IT Firm Study – Aggregated Social Support

3.1. Study Description

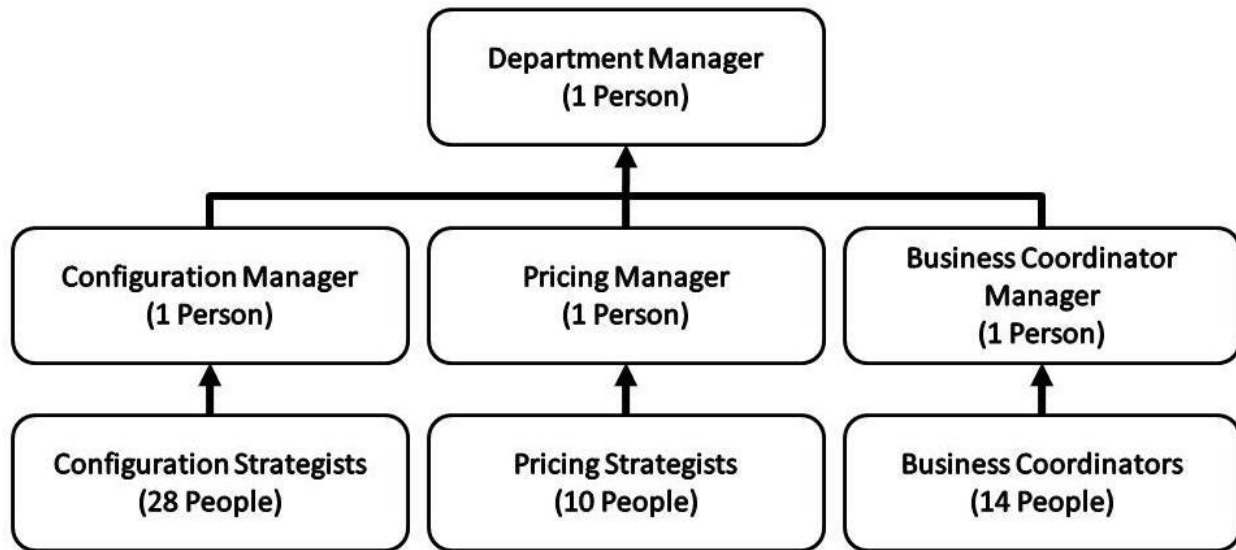


Figure 5. Organizational Chart of the IT Server Configuration Department.

We studied a data server configuration facility with 56 employees, 36 of which participated in this study. The organizational chart of the division can be seen in Figure 5. While the job description of employees at the facility is heterogeneous, we focus on a set of employees whose primary role is to guide, solicit, and fulfill clients' IT configuration requirements. This group consists of 28 people, 23 of whom participated in the study. Interviews indicate that the data configuration process is information-intensive, requiring employees to quickly analyze the feasibility of specifications and build the system. Our onsite interviews with both managers and configuration specialists indicate that talking to other employees is particularly helpful for understanding how the overall system works, how requirements fit together, and how interoperability constrains the set of viable specifications, as

there are no existing manuals to explain all the intricacies of the system. Employees therefore engage in face-to-face communication to transfer tacit and embedded knowledge.

Each configuration task is executed by a single individual and is randomly assigned given a workload constraint, much like a series of queued tasks. In this setting, everyone in the configuration division is placed in a large room with four rows of cubicles. Each row has 4 pairs of cubicles with each pair facing each other. Since everyone is collocated in the same room, there are ample opportunities to meet face-to-face.

To measure worker performance, we collected data on 1217 configuration tasks during the experimental period of 25 working days (more than one month's activities at the facility). For each task, we gathered data on the task duration, difficulty level, the number of follow-ups the employee conducted with the sales team, and information about the employee who performed the task. Although some of the tasks took less than a day to finish, tasks that took more than one day deserve special consideration as we cannot assume the worker is working on the task 24 hours a day. To better approximate the completion time of tasks that span multiple days, we assumed an 8-hour workday. Our interviews with staff indicate that employees typically follow this work schedule and rarely stay late or work on weekends to catch up. Although task completion time is only one dimension of work performance, it is an important outcome in the computing industry (Eisenhardt and Tabrizi 1995), and in this organization employees are formally evaluated on this metric.

3.2. Methods¹

Combining task performance and network data, we empirically test whether face-to-face and proximity networks are correlated with productivity and performance. Time to task

¹ This analysis was performed with Lynn Wu in (Wu, Waber, et al. Under Review)

completion, captured by a computer program that logs the start and end time of each task, measures how fast a person can finish a given task. Based on our interviews, speed is a good measure of work performance in this setting. The accuracy or quality of configurations is also an important measure, but only 20 of the 1217 tasks in our sample contain detectable errors and 90% of those errors were due to server configuration issues that are largely outside the control of individual workers. Since the majority of the tasks are completed correctly, completion time is a good metric for work performance. Although multitasking can increase total task throughput and could confound the use of duration as the only performance measure (Aral, Brynjolfsson and Van Alstyne 2006) in this setting multitasking is not possible since tasks are assigned to workers one at a time. Consequently, task duration provides a good overall measure of work performance that is also relied on by the firm to evaluate employees.

Characteristics of Tasks

As harder tasks take longer to finish, task difficulty is strongly correlated with time to completion. We include two controls for task complexity: *task difficulty* and *the number of follow-ups*. Managers determine the task difficulty based on the initial request and parameters of the job and assign one of three difficulty levels to each task—basic, complex, or advanced. These difficulty ratings can be revised during task execution, although most task complexity scores are never modified. Instead, another metric, the number of follow-ups with the sales team, is used to approximate the complexity level of the task during execution. When tasks are particularly complex, the number of follow-ups between the IT worker and the sales team increases. We therefore include controls for both the assigned (and revised) task complexity and the number of follow ups that occurred during the project.

Although managers assign one of three complexity levels to all tasks: Basic (Low Complexity), Complex (Medium Complexity), and Advanced (High Complexity). The majority of tasks performed in our sample are basic tasks. Basic tasks can be completed quickly, usually in one day, since these jobs are generally straightforward and routine tasks that do not require any advanced technical skills. Often these basic configurations are components of a larger system and workers only need local knowledge about the component, rather than of the entire system, to successfully configure the product. To complete these tasks, workers can use simple off-the-shelf configurations or follow detailed instructions already created by the sales team or the client. Even if they encounter technical difficulties during the task, IT workers can find most of the solutions in existing manuals or knowledge databases. Rarely do they need to consult others to solve these problems. Thus, completing simple tasks usually only requires codified and context-independent information. The difficulty of a complex task lies in between advanced and basic tasks. In our sample, only less than 10% of the tasks are labeled as complex tasks, while the rest are labeled as either advanced or basic.

Advanced tasks are the most difficult tasks, although like all other tasks they are assigned to the first available employee, not based on skill. They are often novel and technologically complex configurations that require more advanced system knowledge. Special and customized orders to build an entire hardware system are typical examples of these tasks. To design these configurations, the IT worker needs to understand the entire system, especially the compatibility of various components within the system design. Solutions in such configuration tasks are usually new innovations that cannot be found in existing manuals or database. These tasks typically take longer to complete than simple routine tasks and the configuration specialist often must confer with other team members to create a viable solution.

Some tasks are classified as advanced not necessarily because of their technical difficulty but because the task description is vague. In addition, customers may impose a budget constraint. To put together a system with a set of functionalities under budget can be challenging and sometimes infeasible. When it is impossible to meet the customer demand, the configuration specialist often contacts the sales representative to clarify which of the customer's requirements are absolutely necessary. The sales team would then work with the customer to revise the requirements or the budget before the IT worker can complete the order. Sometimes, the customer's specifications may have errors and the IT worker would also need to contact sales to verify and modify the existing plan, with the salespeople acting as an intermediary with the customer. To keep track of these exchanges between sales and the IT worker, we measured *the number of follow-ups* in each configuration task, which provides another proxy for task complexity as measured during task execution. Thus, completing advanced tasks and tasks that require frequent follow-ups would take longer than simple tasks as advanced tasks requires the transfer of tacit and embedded knowledge.

The correlation between task difficulty assigned by the manager and the number of follow-ups is 0.7 and their Chronbach alpha is 0.75. We therefore aggregate task difficulty level and the number of follow-ups into a single construct to measure task complexity. We create the task complexity variable by first de-meaning each variable and then dividing each variable by its standard deviation (norm). We then normalize the sum of these variables to construct the overall task complexity.

$$Complexity = Norm(Norm(TaskDifficulty) + Norm(NumberOfFollowUps))$$

Characteristics of Individuals

We included controls for human capital using functional titles that classify employees into 3 categories: manager, pricing strategist and configuration specialist. While managers may be knowledgeable about the entire system, they are less likely to be intimately familiar with day-to-day configuration routines. The primary role of a pricing strategist is to determine if the pricing is feasible and correct based on the requirement, but they perform some configuration tasks as well. Among the three types of workers in our sample, the configuration specialist is most prepared to execute the configuration and we expect them to complete tasks more quickly and accurately. Our interviews indicate that almost all workers have at least a Master's degree in a relevant field such as computer science or computer engineering and all had joined this particular division less than a year before the start of the study. Thus, there is little variation in education level, experience, or tenure within the group.

To mitigate the lack of complete demographic data on workers, we infer some worker characteristics from the badge data. By measuring the tonal variance of workers, we can infer how animated a person is (Pentland 2006). The animation of a worker's voice may give us indications about his general enthusiasm or motivation (Pentland 2006).

Duration Model

Since our dependent variable is the number of minutes it takes to complete a task, we specify a duration model. We use a hazard rate model of the likelihood of a project completing at time t , conditional on it not having been completed earlier. The Cox proportional hazards model is used to examine the effect of network characteristics on project completion rate as follows:

$$\text{Hazard Rate}(R) = f(\text{size, betweenness, constraint, reach, tie strength, complexity, job title})$$

$$R(t) = r(t)^b e^{\beta X}$$

where $R(t)$ represents the project completion rate, t is project time in the risk set, and $r(t)^b$ is the baseline completion rate when all the independent variables are set to zero. In this model, the effects of independent variables are specified in the exponential power, where β is a vector of estimated coefficients on a vector of independent variables X . β has a straight forward interpretation, where $|\beta-1|$ represents the percentage increase (or decrease) in project completion rate associated with a one unit increase in the independent variable depending on whether $\beta-1$ is positive (or negative).

We estimate hazard rate models at the project level with the duration of each project as the dependent variable and a project/worker as the observation. When a coefficient is positive in this model, it means the variable whose parameter is being estimated is associated with more time to complete projects. As employees work on more than one task during the observation period, standard errors are clustered around individuals.

3.3. Results

Table 1 shows summary statistics of the data that we collected. Table 2 shows the effect of the latent cross-sectional network on worker productivity. Unsurprisingly, complex tasks take longer to complete on average. As predicted, network constraint calculated at the individual level is positively correlated with work performance. Instead of reducing speed and productivity, as shown in email networks (Aral and Van Alstyne 2010), a one-standard-deviation increase in face-to-face network constraint is associated with doubling the speed of task completion, demonstrating that network constraint in face-to-face networks is *more* highly correlated with productivity than networks with structural holes. We suspect that the information transmitted in face-to-face networks is inherently different from that which is transferred in other media. It

appears that the advantages of using face-to-face communication to transmit complex knowledge are enhanced in cohesive networks, supporting Hypothesis 1.

Variable	Mean	Std. Dev	Shapiro-Wilk's Statistic
Task completion time ²	515.91	968.89	0.87***
Task Complexity	1.44	0.76	0.55***
Number of Follow-Ups	4.61	3.27	0.92***
Voice Animation	6703509	6056288	0.84***
Interactions	526.62	421.52	0.68***
Network Size	11.44	3.47	0.97
Betweenness	1.49	1.38	0.81***
Network Constraint ²	0.53	0.19	0.87***
2-Step Reach	86.73	7.52	0.52***

Table 1. Summary statistics. Task completion time is in minutes. $N = 931$ for badge related variables, $N = 1201$ for other variables, two-tailed test. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$

Independent Variable	Hazard Rate β
Task Complexity	.565*** (.027)
Tonal Variation	1.000 (6.63e-09)
Interactions Volume	1.000 (.0001)
Network Size	.901*** (0.026)
Network Constraint	2.075** (.603)
Betweenness Centrality	1.135** (.067)
2 Step Reach	1.037*** (0.010)

² When task complexity is taken into account, completion time is normally distributed. Network constraint also becomes normal if an outlier is removed, but this does not change the results so we leave all data points in to be conservative.

Strong Ties	1.225*** (0.092)
Observations	911

Table 2. The Effect of Face-to-Face Networks on Performance. $|\beta-1|$ represents the percentage increase (or decrease) in project completion rate associated with a one unit increase in the independent variable depending on whether $\beta-1$ is positive (or negative). Standard errors in parentheses. $N=931$. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

The Effect of Network Structure on Completing Complex Tasks

As cohesive networks enable more effective transfers of complex knowledge (Reagans and McEvily 2003) we expect network constraint to be more effective when employees are engaged in complex tasks. Given the cost of face-to-face interactions in time, effort, energy, and interruption, we also expect additional face-to-face interaction, especially those with strong ties, to increase the speed of project completion for complex tasks that require more information, advice, and tacit guidance from colleagues. For complex tasks, we expect the benefits of face-to-face conversations to outweigh the costs, whereas for simple tasks we expect there to be less benefit to interaction, while still creating costs. To test these expectations, we add interaction terms between task complexity levels and various network measures. The results in Table 3 lend broad support to our hypotheses.

Independent Variable	Hazard Rate β
Task Complexity	0.102* (0.120)
Tonal Variation	1.000 (7.04e-09)
Interaction Volume	1.000 (0.000167)
Network Size	0.864*** (0.0276)
Network Constraint	2.080** (0.657)
Betweenness centrality	1.224*** (0.0819)
2-Step Reach	1.041*** (0.0112)
Strong Ties	1.293*** (0.102)

ComplexityX Interact. Vol.	1.000 (0.000138)
ComplexityX Network Size	1.040 (0.0336)
ComplexityX Network Constraint	1.796* (0.623)
ComplexityX Betweenness	0.988 (0.00942)
ComplexityX Reach	1.012 (0.0136)
ComplexityX Strong Ties	0.981 (0.0665)
Observations	911

Table 3. The Effect of F2F Networks on Work Performance in Complex Tasks. $|\beta-1|$ represents the percentage increase (or decrease) in project completion rate associated with a one unit increase in the independent variable depending on whether $\beta-1$ is positive (or negative). Standard errors in parentheses. $N=931$. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

In the cross-sectional network, we find that network constraint continues to have a positive correlation with the rate at which tasks are completed, and is especially beneficial for completing complex tasks. The interaction term between task complexity and network constraint is positive ($\beta=1.796$, $p<0.1$), demonstrating that face-to-face network constraint may facilitate transferring and understanding complex information.

3.4. Discussion

In this study we showed that in face-to-face networks, constraint, rather than structural holes, is associated with higher productivity. We suspect that information transmitted in face-to-face networks is more tacit, complex, and embedded than information transferred through electronic channels, and that the advantages of using face-to-face communication to transmit complex knowledge are enhanced by network constraint which increases norms of trust, effective communication heuristics and absorptive capacity through the provision of multiple perspectives on a problem. We also find that face-to-face network constraint is more strongly correlated with performance when the participants are solving complex problems. This suggests

that network constraint complements information-rich communication media for the effective transmission of complex tacit knowledge when conducting complex tasks.

It is always difficult to attribute causality with correlational results. In our next study we go beyond these results by studying changes in networks over time, showing that changes in network constraint are strongly associated with changes in outcome.

Chapter 4

German Bank Study – Changes in Social Support

4.1. Changes in Communication Patterns

One challenge to the network approach is that communication patterns change so frequently that observing interactions at an aggregated level does not reveal what dynamics are key drivers of outcomes. As we discussed, different phases of a project require different collaborative structures (Ancona, Bresman and Kaeufer 2002). However these changes in communication patterns may have unintended consequences. While a diverse network rich in structural holes may be useful for gathering information, it could also weaken social support.

Random factors also influence how communication patterns change. Vacations, individual moods, and workload influence how much time people are willing to devote to communication, as well as what type of communication they want to engage in. The arguments laid out above from media richness theory posit that such changes in interaction patterns, while small, should impact job satisfaction.

There is ample evidence that short-term changes in communication patterns affect individuals from affective events theory (AET). AET posits that organizational events cause most of the changes in affect in employees (Weis and Cropanzano 1996). Subjects in affective events studies keep a journal cataloging noteworthy events throughout the day, taking note of face-to-face interactions, recognition events, and observed acts by other employees that generated an affective reaction. Basch and Fisher (Basch and Fisher 1998) examined categories of these events and over 50% of the events reported by employees were related to interpersonal communication. While in the present study we do not know what the affective contents of an

interaction are, we can estimate their effect on an individual's job satisfaction by examining how this interaction changes an individual's network. From our first hypothesis we can infer that in terms of face-to-face communication if the interaction increases network constraint then it was a positive interaction while if it decreases network constraint it was a negative interaction. We are not suggesting that the interaction itself was negative or positive per se, but that the overall effect of the interaction will be positive or negative in the longer term due to the relationships between network constraint, social support, and role conflict and ambiguity.

Evidence from Baumeister and Leary (Baumeister and Leary 1995) suggests that strong relationships that persist or increase in strength over time increases an individual's sense of belonging and by extension in a work environment positively affecting their job satisfaction. The strength of a relationship has been shown to directly relate to network constraint (Louch 2000), further indicating that changes in face-to-face network constraint should be related to changes in job satisfaction.

But does this pattern extend to e-mail communication? Gloor and his coauthors found that in an online collaborative game changes in communication network structure over two week intervals did not relate to team performance (Gloor, et al. 2008). While the communication that occurred in this game sits in between e-mail and face-to-face communication in terms of richness, it is nonetheless indicative of a gap in the ability of computer mediated communication to allow individuals to affect outcomes dynamically.

Media richness theory posits that e-mail communication is good for discussing routine technology, and thus we would expect e-mail communication patterns to remain relatively stable over time. Matters of greater urgency or that deal with a dynamically changing situation would by definition be a low analyzability task and so would be better suited for face-to-face

communication. The network property of betweenness, which is beneficial in an e-mail network, cannot adequately capture communication dynamics over short periods of time because it relies precisely on weak links that are not activated often for its predictive power (Granovetter 2005). This further implies that e-mail communication changes will not be related to any substantive outcome changes over short periods of time.

In short, our previous hypothesis utilizing media richness theory as well as the relationship between network constraint, relationship strength, and job satisfaction leads us to believe that changes in face-to-face network constraint will be positively related to changes in job satisfaction. We do not expect changes in e-mail communication to relate to changes in job satisfaction because previous studies imply that electronic communication changes do not relate to changes in outcomes and that changes in centrality rely on communication that is infrequent, and thus unlikely to occur during short time intervals. We formally state our hypothesis as:

Hypothesis 2: Changes in short-term job satisfaction are positively related to changes in face-to-face network constraint.

4.2. Germany Study Description

We deployed the Sociometric Badges for a period of one month (20 working days) in the marketing division of a bank in Germany that consisted of 22 employees (8 women, 14 men) distributed into four teams, a management group, and an intern that was outside of the hierarchical structure. One male subject left the company shortly into the study, so we subsequently exclude that subject's data from the analysis for a total of 21 employees. All of the managers in this division were men.

The division contained four functional teams consisting of either three or four employees. Each of these teams was overseen by a manager, who was in turn supervised by a mid-level

manager. These mid-level managers were responsible for two teams, and they reported directly to the division manager. The division's organizational chart is shown in Figure 6.

In this division the makeup of the various teams is somewhat different in their work approach. The development, sales, and support teams are much more collaborative in their work style and the nature of this work is much more creative than that of the people on the customer service team, which focus more on directly interacting with customers and branch employees over the phone.

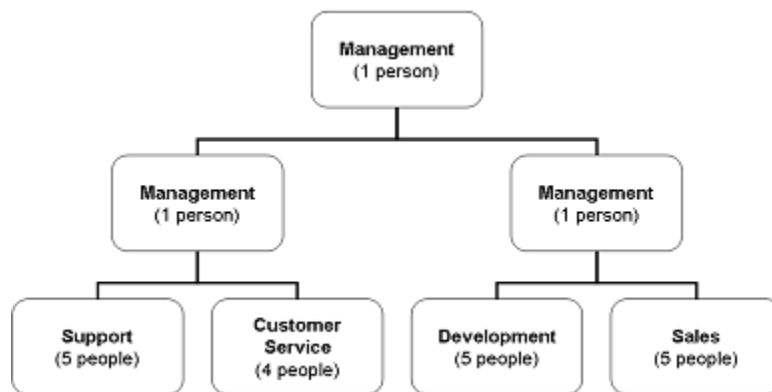


Figure 6. Organizational Chart of the German Bank's Marketing Division.

Over the course of the study this division was developing and rolling out a campaign for a variety of new banking products. They were particularly focused on deploying online marketing campaigns, and they have recently begun to integrate social media components into their overall strategy.

The sales team developed campaigns as well as created new product packages that could be effectively marketed. This team consisted of employees with a design and marketing background in addition to their banking education. Members of the development team created a suite of web-based advertisements to increase awareness of these campaigns, and the team consisted of a mix of graphic designers, programmers, and bankers. The customer service team handled contracts and legal work for the department while also serving as a contact point for

branches when customers inquired about online banking services. Finally, the support team served mostly as administrative assistants for the department. The members of this division in general came from very diverse backgrounds, and in this sense it typifies what we envision as the future of teams.

This young and fast-growing division was eager to experiment with their organizational structure, and they had previously run a number of internal studies using e-mail communication to determine better ways to organize themselves. By adding the Sociometric Badges to this mix they were able to get an even more complete view of their behavior. This may represent a trend for teams in the future where sensor and electronic data is combined to act as a powerful reflection and intervention tool.

Each employee was instructed to wear a Sociometric Badge every day from the moment they arrived at work until they left their office. In total we collected 2,200 hours of data and 880 reciprocal e-mails. We obtained these e-mail logs as well as self-reported individual and group performance satisfaction data as part of a case study on the impact of electronic communications on the business performance of teams (Oster 2007). In our dataset we only collected e-mail data on intra-division communication due to confidentiality concerns. Confidentiality requirements also prevented us from capturing subject lines and message content. For our study we collected 880 e-mails and we removed 91 e-mails (approximately 10%) that were not reciprocated.

The bank division itself also had an interesting physical layout. The division was split across two floors with 6 rooms on the second floor and 4 rooms on the third floor. Some teams were co-located in a single room while others had employees from multiple teams in them.

Study Protocol

The Sociometric Badges logged IR detections (containing the transmitting badge's ID) every time they were facing other badges, Bluetooth devices' IDs, motion data from the accelerometer, and audio signals. The audio signal was sampled at 8 kHz and averaged over 64 samples so that the raw speech signal could not be reconstructed in order to maintain privacy. All collected data was anonymized and each participant had access only to their own data upon request.

In addition to the 22 wearable badges, 14 badges were used as base stations and placed in fixed locations across two floors of the bank's building to roughly track the location of interaction events as well as subjects. Base stations were continually discoverable over Bluetooth. A central computer was used for data collection and was placed in the division's conference room, where employees could easily retrieve their badges when they arrived and plug them into a USB hub before they left for the day. This operation allowed data to be automatically transferred via the badge's USB port and securely uploaded to a server in our laboratory once a day, while at the same time recharged the badge's battery. In this experiment we used e-mail as a representative proxy for electronic communication since it was the most frequently used means of communication among employees in this organization.

At the end of each day employees were asked to respond to an online survey that consisted of the following questions:

- Q1.** What was your level of productivity today?
- Q2.** What was your level of job satisfaction today?
- Q3.** How much work did you do today?
- Q4.** What was the quality of your group interaction today?

Each question could be answered according to the following 5-point scale: (1 = very high) (2 = high) (3 = average) (4 = low) (5 = very low). In our analysis below we flipped the scale (i.e. |6 - previous value|) for ease of interpretation. These questions had been used for another study within the company and management wanted to minimize the amount of time spent by employees answering surveys. Since these surveys were taken daily, lowering complexity was very important, and these questions have been used in previous studies (e.g. (Van der Vegt 2002); (Churchill, Ford and Walker 1976)). Meta-analyses have also shown that findings on job satisfaction are robust to the type of measure employed (Judge, Heller and Mount 2002). Other meta-analyses have also validated the use of a single-item measurement of job satisfaction (Wanous, Reichers and Hudy 1997); (Scarpello and Campbell 1983).

Table 4 lists the summary statistics of the data that we collected.

Variable	Mean	Std. Dev	Shapiro-Wilk's Statistic
Job Satisfaction	3.43	0.37	0.91
Productivity	3.51	0.30	0.96
Workload	3.39	0.39	0.95
Quality of Interactions	3.83	0.57	0.94
E-Mail Network Constraint	0.28	0.11	0.88*
E-Mail Betweenness	1.28	1.26	0.85**
Total E-Mails	24133	19530	0.64***
F2F Network Constraint	0.57	0.28	0.86**
F2F Betweenness	0.50	0.21	0.90*
F2F Interaction Time	87.12	94.28	0.75***

IR Contribution Index	0.01	0.42	0.96
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Table 4. Summary statistics. Face-to-face interaction time is shown in hours. $N = 21$, two-tailed test. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

Data Panels

Most subjects did not participate every day of the study, and in addition it takes time for social network patterns to stabilize. Following Gloor (Gloor, et al. 2008) who showed that two weeks was the minimum amount of time for network communication patterns to stabilize in group communication, we split the data into two successive two-week panels. This smoothed over daily participation variance as well as provided a maximum number of subjects that participated in both halves. Performing analyses at the week level yielded comparable results.

We averaged the survey responses from both halves to get a more robust look at the subjects' job satisfaction over that period of time. For the IR and e-mail data we formed social network representations from the data taking into account only interactions that occurred in the first two weeks or the second two weeks for each panel respectively.

We took the difference scores between the survey averages in the first half and the second half, and similarly performed this with the social network features we computed for each communication medium. The additional accuracy obtained through behavioral data collected with the Sociometric Badge allows us to be confident of the results and to use difference scores for ease of interpretability. Table 5 shows the summary statistics for this data.³

Variable	Mean	Std. Dev	Shapiro-Wilk's Statistic
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³ Importantly, the survey differences were normally distributed but network constraint and communication amount differences were not. Removing two outliers in the data resulted in them satisfying the normality condition for the network constraint variable and increased the strength of our results. Removing three outliers for the total face-to-face communication amounts normalizes that variable, as does removing one outlier from total e-mail communication amount. Removing these outliers increases the magnitude of the correlations between total e-mails and job satisfaction and other survey responses, but the relationships are still not significant. For total face-to-face interaction, removing outliers slightly reduces the magnitude of the correlation with job satisfaction, but all other correlations are nearly identical. To be conservative we report all results with all subjects and data points included.

Job Satisfaction	-0.36	0.46	0.94
Productivity	-0.32	0.39	0.97
Workload	-0.11	0.53	0.97
Quality of Interactions	-0.25	0.45	0.96
E-Mail Network	0.01	0.07	0.84**
Constraint			
Total E-Mails	1433	7912	0.65***
F2F Network Constraint	-0.16	0.43	0.81**
F2F Interaction Time	54	105	0.71***

Table 5. Summary statistics for panel difference data. Face-to-face interaction time is shown in hours. $N=21$, two-tailed test. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

4.3. Results

In order to test the relative effects of work-related features, e-mail, and face-to-face communication in affecting job satisfaction, we performed a multiple linear regression for the month-long and panel cases, where we include survey results, a dummy variable to distinguish managers from non-managers, and the badge and e-mail features described above.

In Table 6 we show the pairwise linear correlations between the variables that we test when we aggregate data over the course of the entire study. All of the variables except betweenness, total e-mail, and face-to-face interaction time are normally distributed.

Variable	Job Satisfaction	Productivity	Workload	Quality of Group Interaction	E-Mail Network Constraint	E-Mail Betweenness	Total E-Mail	F2F Network Constraint	F2F Betweenness	F2F Interaction Time	IR Contribution Index
Job Satisfaction	-										
Productivity	0.31	-									
Workload	0.14	0.92***	-								
Quality of Group Interaction	0.69***	0.51*	0.40	-							
E-Mail Network Constraint	0.31	0.52*	0.48*	0.54*	-						

E-Mail Betweenness	-0.47*	-0.08	-0.02	-0.51*	-0.29	-					
Total E-Mail	-0.33	-0.3	0.00	-0.25	-0.20	0.67***	-				
F2F Network Constraint	0.10	0.10	0.00	0.16	0.11	0.13	0.27	-			
F2F Betweenness	-0.13	-0.23	-0.40	-0.36	-0.14	0.23	-0.03	0.23	-		
F2F Interaction Time	-0.04	-0.30	-0.34	-0.11	-0.29	0.23	0.58**	0.55**	0.09	-	
IR Contribution Index	0.02	-0.23	-0.13	-0.16	-0.23	0.44*	0.40	0.09	-0.03	-0.03	-

Table 6. Aggregate data over entire study. $N=21$, two-tailed test. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

In Table 7 we examine the correlations between the differences across the two panels.

Variable	Job Satisfaction	Productivity	Workload	Quality of Group Interaction	E-Mail Network Constraint	Total E-Mail	F2F Network Constraint	F2F Interaction Time
Job Satisfaction	-							
Productivity	0.18	-						
Workload	0.08	0.81***	-					
Quality of Group Interaction	0.32	0.11	-0.03	-				
E-Mail Network Constraint	-0.07	-0.19	-0.16	0.08	-			
Total E-Mail	0.07	0.18	-0.09	-0.08	-0.32	-		
F2F Network Constraint	0.72***	0.15	0.15	0.18	-0.23	0.20	-	
F2F Interaction Time	0.31	0.03	-0.23	0.18	-0.32	0.66**	0.53*	-

Table 7. Differences across panels. $N=21$, two-tailed test. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

Next we show the results of our multiple linear regression with the panel data differences in Table 8, where change in job satisfaction is the dependent variable. We created a binary variable “manager” that is coded 1 if the subject was a manager and 0 otherwise.

Variable	β
Intercept	-0.13
Productivity	0.37
Workload	-0.30
Quality of Group Interaction	0.17

Manager	0.28
E-Mail Network Constraint	0.23
Total E-Mail	$8.2 \cdot 10^{-6}$
F2F Network Constraint	0.81**
F2F Interaction Time	$-3.7 \cdot 10^{-7}$
Model R ²	0.66
Adjusted R ²	0.43
F	2.89*

Table 8. Multiple regression for panel data. $N=21$, two-tailed test. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

The results above clearly show that changes in job satisfaction correlate strongly with changes in network constraint as detected by the Sociometric Badge but not with e-mail features, confirming Hypothesis 2. While baseline levels of job satisfaction are predicted by a variety of factors, it appears that changes in face-to-face communication may be a major factor in changes in job satisfaction. Changes in e-mail network constraint showed no significant correlation with changes in job satisfaction. This may be because interactions over e-mail tend to be more formal and changes in e-mail patterns would not imply social or mood changes that would affect job satisfaction. This also implies that task-related job changes that might be reflected in the more formal e-mail communication structure do not appear to be associated with job satisfaction in this setting.

4.4. Discussion

One of the pressing problems facing organizations today is how to shift face-to-face interaction into the online space. E-mail and other communication tools are frequently praised for the flexibility that they offer employees, enabling telecommuting, distance teams, and

creating completely new organizational forms. Frequently decisions are made to embrace these technologies without considering what is lost when face-to-face interaction is reduced.

As predicted by Hypothesis 2, changes in face-to-face network constraint were highly predictive of changes in job satisfaction. Changes in communication patterns may be brought on by changing team projects, vacations, and the like, and so it may be that these changes are indicative of situations where an individual is experiencing increases or decreases in social support, role conflict, and relationship strength. If these issues are typically resolved in a short amount of time, however, then we would expect to see the relationship between network constraint and job satisfaction at the dynamic level but not at the aggregate level.

These changes did not appear to affect e-mail communication in any significant way, and as hypothesized changes in e-mail communication had no affect on changes in job satisfaction. It may be that less rich communication media are not adequate for resolving issues such as role conflict and increasing social support over short periods of time. This has strong implications for teams that are considering shifting to a more distributed collaboration model, since these results imply that while individual phases of a project can be supported by e-mail communication, changes in these phases needs face-to-face interaction to allow a smooth transition. In future work it will be important to collect detailed project data and to ask subjects questions about role conflict and social support to validate this interpretation.

We also have shown the same results using data from the Chicago IT firm (Wu, Waber, et al. Under Review). In particular, using the task-level data we showed that changes in network constraint were positively correlated with changes in productivity as measured by completion time. This lends further strength to our results here.

In this study we hoped to get closer to determining the causality of these correlations by analyzing the data using panels. Combined with our results that we previously described from a completely different kind of organization with a completely different culture, we can be more confident that this represents a general human condition.

It is also important to consider the context of this particular organization. These teams were co-located and worked under a well-defined formal hierarchical structure. In organizations where formal relationships are murkier, one could imagine that high network constraint might lead to cliques and a fractious work environment.

For teams that rely heavily on electronic communication it is certainly possible that different effects would emerge. In these teams face-to-face interaction would be rare and most likely very task-centric, so other externalities that often emerge may not be present. Similarly, in geographically dispersed teams face-to-face interaction is often impractical so only electronic communication mechanisms can be employed, and as we discussed above the transition from face-to-face interaction to distributed collaboration could be eased with additional communication channels.

One could argue that higher levels of job satisfaction lead to higher network constraint because people interact more with their peers when they are happier. This is unlikely because this effect would also have to spread directly to an individual's neighbors and cause them to interact more with the peers of the individual who originally had the change in job satisfaction. Previous ethnographic studies support our position, with Roy (Roy 1959) showing that increased informal communication within a workgroup causally increased job satisfaction. A natural question is how to practically apply these results. There are numerous strategies one can undertake to increase network constraint. The tension is that because this communication is

informal, formalizing the processes that facilitate this kind of interaction may reduce its effectiveness. Relatively simple strategies, such as aligning employee breaks or scheduling an office-wide coffee break one day a week, could have strong effects. These interventions would have the benefit of being an informal context for employees to socialize while still being a formal mechanism that the organization can implement. Next we discuss such an intervention and its effect.

Chapter 5

Call Center Study – Changing Social Support

The positive effect of strong social groups in face-to-face networks on productivity has been observed in many different settings, as documented by (Reagans and Zuckerman 2001). While in our previous studies we demonstrated how changes in face-to-face network constraint were positively associated with changes in job satisfaction and productivity, since this was a correlational result we could not definitively say that this effect was causal. In this chapter we present a two-phase study undertaken to experimentally study in a real world setting the effects of face-to-face network constraint and how to increase network constraint in the workplace.

In the first phase of our study, we measured interactions between workers at the call center of a large bank based in the United States using Sociometric Badges (Olguin Olguin, Waber, et al. 2009). We were also able to obtain demographic data, psychological survey responses, as well as detailed productivity data from the company. We confirmed our hypothesis that the strength of an individual's social group was positively related to productivity (average call handle time) for the employees that we studied.

We studied employees from four teams of roughly 20 people each. Originally each employee on a team had a separate 15 minute break during the day. The breaks were separate so call loads did not have to be shifted significantly to other teams, however this bank has over 10,000 call center employees, so this is not an important issue for the company. Unfortunately, this break structure made it very difficult for cohesive relationships to develop, since groups of friends will by design have limited opportunities for shared interactions.

To create more of these opportunities we changed the break structure of two of the four teams after the first phase of the study so that all of the employees on a team are given a break at the same time. After giving this change three months to stabilize, we returned to the call center and measured the behavior of the employees again using Sociometric Badges. Our hypothesis is that this change will not only increase individuals' network constraint but also increase their productivity.

5.1. Theory

Breaks

Call center employees are put under a large amount of psychological pressure in their job (Wallace, Eagleson and Waldersee 2000). Not only do they have to deal with a never-ending stream of unhappy customers, but they must also deal with a management system that frequently sacrifices employee well-being for short term results (Wallace, Eagleson and Waldersee 2000). It is also difficult for these employees to spend time venting with their fellow workers, since breaks are often staggered to prevent lapses in call center coverage.

Many call centers today, however, have grown large enough so that individual teams do not have one specialty, and call loads can be easily shifted between teams at no cost to the organization. Despite this, policies of only allowing one employee on a team to be on break at a time persist.

Breaks themselves are often viewed in the literature as an individual function. Breaks function to allow employees to recharge (Dababneh, Swanson and Shell 2001), avoid injury (Hedge 1999), etc. The emphasis in operations research is usually on minimizing break overlaps (Dababneh, Swanson and Shell 2001), and little regard is given to the idea that social interaction

during breaks provides the employee with a valuable opportunity to discuss difficult issues as well as exchange knowledge about their job.

Social Networks at Call Centers

Some researchers have suggested that promoting high turnover at call centers improves performance (Wallace, Eagleson and Waldersee 2000). The authors lament that call centers require strong supportive management systems to stave off employee burnout, which is arguably costlier to implement than retraining new, more motivated call center employees. We believe that the answer to this problem is not a formal mechanism at all, but rather simple management practices that support the creation of an informal support structure. By changing the break structure of call center employees, we will show that we can increase the strength of these social ties and by extension increase their productivity and job satisfaction all at no cost to the organization.

Break Structure

Ergonomics researchers have an extensive history examining break structure at work, particularly for physically demanding jobs (Hedge 1999). In laboratory studies workers performed best if they were allowed to choose their own breaks, and this was confirmed in several real-world studies (Hedge 1999). Importantly gains were also realized in terms of worker physical health, implying that there might be similar gains for mental health, which is an important factor in job satisfaction (Sullivan and Bhagat 1992).

Other researchers examined changes in break structure at a meat processing plant, finding that having longer break periods distributed throughout the day were more effective than a larger number of short breaks (Dababneh, Swanson and Shell 2001). While this was not examined in

the paper, we hypothesize that a potential benefit of the longer breaks were more opportunities for meaningful interactions, which would have been difficult to engage in during shorter breaks.

A large number of models treat the workforce as a homogeneous group when making scheduling decisions such as breaks, particularly in the case of telephone operators (Baker 1976). Staffing decisions are not made in a vacuum, but they tend to emphasize staff requirements and other formal concerns (Baker 1976). We believe that the informal context (who is important from the perspective of the social network of the group) deserves consideration even in jobs that are typically not viewed as having a strong social component.

In particular, we hypothesize that:

Hypothesis 3: Scheduling employee breaks to overlap for people on the same team will lead to stronger social groups.

5.2. Study Description

We ran a two phase study at a call center of a major North American banking firm with over 3000 employees located in the northeastern United States. During the first phase of the study we targeted four teams at this call center, each consisting of around 20 employees. 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. The executives in charge of the call center unit of this bank had the intuition that limiting interaction for the call center employees during break periods had negative effects on the mental well-being of the employees and may lead to higher turnover.

The structure of breaks for these employees, as in many call centers, was to reduce as much as possible the overlap between breaks for people on the same team. Each employee was given one 15-minute break per day in addition to a 30 minute lunch break. This organization has over 10,000 call center employees, so shifting call loads has greatly reduced in importance over time.

The four teams were each headed by a single manager, who had a desk in the group area. Employees sat in cubicles in front of a computer terminal taking customer calls on a variety of banking issues.

In addition to the Sociometric Badges, we obtained productivity data from the call center which is automatically logged by an enterprise software system. The measure of productivity we will use here is average call handle time (AHT), which represents the cost of running a call center. For example, reducing AHT by 5% at this call center would save this company roughly one million dollars. 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.

5.3. Results

For the first phase of this study, we first wanted to discover whether or not face-to-face interactions had any effect on productivity or stress levels. We performed a linear correlation analysis to determine the relationship between these features, and the results are shown in Table 9. For the gender variable females were assigned the number 0 and males were assigned 1. The amount of interaction variable represents the number of seconds of face-to-face interaction that were detected over the course of the study. Tenure is measured in days since the employee was hired. For each correlation we used only individuals that had data for both variables, while in the multiple linear regression below we used only subjects that had data for all variables.

Variable	AHT	Network	Constraint Degree	Betweenness	Amount of Interaction	Stress	Gender	Age	Tenure	Mean	Std Dev
AHT	1	-	-	-	-	-	-	-	-	263	38
Network	-0.61***	1	-	-	-	-	-	-	-	1.07	0.41
Constraint Degree	0.23	-0.48**	1	-	-	-	-	-	-	3.06	2.08
Betweenness	0.21	-0.36	0.53**	1	-	-	-	-	-	1.33	1.76
Amount of Interaction	-0.06	0.08	0.31	0.25	1	-	-	-	-	1214	1608
Stress	0.33*	-0.23	0.25	-0.04	0.06	1	-	-	-	3.07	0.97
Gender	-0.25*	0.10	-0.14	-0.16	-0.14	-0.10	1	-	-	0.67	0.47
Age	0.06	0.24	-0.30	-0.23	-0.24	0.02	0.23	1	-	33.48	12.10
Tenure	0.11	-0.06	-0.05	-0.14	-0.14	-0.09	-0.07	-0.09	1	832	331

Table 9. Aggregate data over entire study. $N=68$, two-tailed test. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

We then performed a multiple regression to predict AHT using network constraint, stress, and gender. The results are listed below in Table 10.

Variable	β
Intercept	296.77***
Network Constraint	-52.15***
Stress	8.57

Gender	-9.40
R²	0.49
Adjusted R²	0.43
F	8.57^{***}

Table 10. Multiple regression results for predicting average handle time. $N=68$, two-tailed test. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

Next we examine if network constraint significantly changed for participants across different waves of the study. While the call center has not yet released performance data to us, the managers have expressed confidence that the new break structure has also enhanced performance. We found that network constraint significantly changed across the different waves of the study ($p < 0.05$) and the mean difference between the two waves was 0.19. Management is currently planning to change all break structures of their call centers to this new system, and they are forecasting a \$15 million/year productivity increase, although we were not able to validate that estimate.

5.4. Discussion

In this study we hoped to get a better understanding of the relationship between the strength of an individual's social group and job satisfaction. While we are still awaiting productivity data from phase two to be able to confirm our third hypothesis, we have shown that this holds in a correlational fashion using data from the first phase of our study. Results from the other studies strengthens the case for causality, although there is clearly a complex set of causes and consequences at work. The fact that stress was also negatively related to network constraint (albeit at a non-significant level) as well as its previously documented positive impact on job satisfaction indicates a number of benefits arising from strong informal social groups.

We also found that tenure was not significantly related to either AHT or network constraint. As has been shown previously, long organizational tenure does not relate to higher productivity in call centers (Castilla 2005) but it is interesting that it does not appear that tenure affects an individual's network constraint. This is counter intuitive, since one would imagine that people accumulate friends in the workplace over time and will build a closed network of friends. Since it appears that strong social groups drive performance, however, it is clear that other management interventions, such as giving employees breaks at the same time, are crucial since this behavior will not necessarily emerge naturally for all people.

Since our manipulation increased network constraint among the study participants, it indicates that serendipitous mechanisms may be a major factor in determining interaction patterns. This is supported by previous ethnographic work (Roy 2003).

We believe that we have shown a natural, low-cost way to increase the strength of social groups in workplaces. Contrary to some previous work, using detailed behavioral data we have shown that strong social groups are beneficial to productivity and can be supported without extensive management interventions.

Chapter 6

Travelco Study – Connecting the Behavioral and Qualitative

6.1. Motivation

After having conducted numerous studies showing that face-to-face network constraint is indeed responsible for changes in job satisfaction and productivity, it is tempting to say that the matter is closed. We have shown correlational results in both aggregated and dynamic contexts, and we have experimentally manipulated behavior to change network constraint. These studies encompass a variety of organizations each with a different cultural context and different employee pool.

The remaining hole to be filled in this argument is that of the mechanism by which face-to-face network constraint actually changes outcomes. As we elaborated above, there are a number of management theories which have been borne out by our data. But if we are asked what is actually happening in our data, what is happening in these organizations that we have observed, the answer is that we don't really know.

This problem is not unique to research with the Sociometric Badge. Surveys do not give any insight into organizational context beyond the questions that are asked. Interviews give a limited and potentially biased view of the organization. With our data, while we know that two people were e-mailing each other and that they spoke to each other at a certain time we don't know the underlying reasons. Was this a serendipitous interaction? Were they talking about something work related? These are questions that are impossible to answer with certainty using only the Sociometric Badges.

It is for this reason that we felt it necessary to combine the strength of the Sociometric Badges, namely robust, fine-grained, and continuous data collection, with the strengths of the ethnographic approach. It turned out to be quite difficult to find a company that would allow us to collect all of this data at the same time. Below I will describe this study in detail, first through participant observation and then using data from the Sociometric Badge and other sources. Finally, I will combine them to give a complete view of the organization and show further insights into the importance of network constraint.

In the participant observation below we use pseudonyms, although gender has been preserved. Some observational data also had to be omitted since it would identify some individuals.

Discovering Travelco

The story of how we came to Travelco is a classic case of serendipity. I had had multiple potential studies fall through for legal as well as cultural reasons. Despondent, I told my friend Sara that I was having no luck finding a study site. She had recently been hired by a growing online travel company, and they were very concerned with improving their culture and understanding the social relationships within their company.

While I was not optimistic, having tasted rejection many times before, I sent an e-mail to her explaining the project in more detail. I was surprised when in a few weeks I had a meeting set up with Andrew and Bill, two executives from Travelco. Initially they were skeptical that we would be able to execute this study, but after a one hour meeting they were sold on the idea and invited me back to meet with Travelco's managers so that we could gauge their reaction and see if we could move forward.

What struck me in this meeting was how concerned Andrew and Bill were with what they called “their culture,” particularly the importance of informal interaction. In most of the other organizations I have visited, they either paid lip service to informal communication or ignored its importance completely. When running a study at a computer equipment firm, for example, the manager of the division I was studying said, to paraphrase: “If it’s not on the organizational chart, it doesn’t matter.”

When asked about what they wanted to get out of the study, management at Travelco responded: “We’re very serious about our culture. We’re always looking for ways to improve it and make it better.” They said they had hired consultants to gauge how people felt about “the culture,” and they would organize informal events and team building exercises with their stated goal to promote interaction.

6.2. Travelco Description

Travelco is a major online travel company, but still relatively small in terms of number of employees. To try to build an international presence they have acquired large travel websites from other countries, but they are still primarily based in the US. Their headquarters, the subject of this study, houses a staff of roughly 70 people, which comprises around half of their total workforce.

Many of the employees at Travelco, and especially the upper level management, have extensive start up experience from the dot com era, and this influence was evident to me as I studied their workplace. Their headquarters is outfitted with the requisite foosball table, and couches are positioned next to a sprawling kitchen area that is stocked with numerous free drinks and snack staples. Travelco’s management even stated they want to “intentionally keep a start-up feel.” Discussions typically have a degree of openness that would be unusual at more

traditional companies. As an illustration of this, of the 72 informal interactions that I observed in their entirety and which I have notes on the content of the exchange, 11 had a direct report challenge the ideas of their superior. Over the course of the study I even observed three games of America's Army (a popular online first person shooter) break out across the office.

Office Layout

Travelco's headquarters is located inside a typical office park which also houses gym and cafeteria facilities. Nearly all employees drive to work, and while many people live relatively close to the office and have a commute of less than 45 minutes, a few have commutes lasting almost 2 hours. There is a stairwell right off the main parking lot that leads to the third floor backdoor entrance of Travelco's office, although the front entrance for visitors is accessible by elevator from the main lobby.

Walking in from the main entrance, you are greeted by a red-tinged room of humming servers on your left. Occasionally when a server goes down one of the technical workers will be in the room, poking at a keyboard, through the glass walls looking like a fish in an aquarium. On the wall to the right are projections of Travelco commercials and flight information from across the country, updated in real time.

The kitchen abuts the server room, and is a sprawling space with a large island in the center where various leftovers and foodstuffs sent from other companies are left for employees to devour. Additional snacks are provided on a counter which runs into a corner where a number of coffee machines are located. There is also a music controller on the island that can be used to choose which songs are being played over the speakers in the kitchen. People at their desks can also control what music is being played. The result is often a strange mixture of conflicting musical genres.

The food in the kitchen acts something like a magnet. I only observed one thirty-minute period where there were no conversations occurring in the kitchen, and across the 34 interactions in the kitchen that I noted 22 of them occurred while one participant was eating food. In 11 of these conversations, someone who was waiting at the coffee machine joined a conversation that was already in progress. People also eat lunch in the kitchen area, either bringing food from home or from the cafeteria on the first floor. Every day that I was present at Travelco at least two groups ate lunch in the kitchen, although I did not observe many of those interactions in their entirety.

Just past the kitchen there are two glass-walled meeting rooms, one on the left for smaller meetings of around 10 people, and the meeting room that is straight ahead accommodating up to 20 people. The smaller meeting room is lined with whiteboards that are often used to sketch out software development or architecture plans. Of the four meetings in these rooms that I attended, no one from Travelco used the projectors, instead favoring oral description of different concepts. Each of these meetings had an interaction style that was closer to that of a presentation, with each individual taking clear speaking turns with little overlap. The larger meeting room can also be opened up for company-wide meetings, with people standing in the hallway and sometimes even being pushed back into the kitchen.

Make a right and you'll be standing next to a few couches and the company foosball table, which is used mostly during and after social events. Straight ahead is the large, open area where all of the Travelco employees sit.

Each employee has their own cubicle, with low, frosted glass walls which allow people to stand up and easily talk to the person sitting on the other side. The desks themselves are fairly long, and arranged so that rows run like chevrons from the main aisle. The rows are positioned

in a step-like fashion, split into segments where four cubicles are grouped together in a rough square, with the aisle of the row running through it.

People spend most of their time at their desks, although there are always small groups of people congregated in the main aisle or people walking to one of their co-worker's desks.

People on the same team are not necessarily in the same row, making for a lot of movement around the office. These groups do talk about both work and personal issues, although in places like the kitchen talk shifts more towards personal issues, and I observed some personal issue being mentioned in all but one interaction in the kitchen.

On the right next to the foosball table are three small rooms for one-on-one meetings. One of the VPs heavily involved in product development sits right in front of these meeting rooms and right next to the main aisle, making it easy for people to come with him for questions. The CTO has his own office two rows down in a corner next to the meeting rooms, but he also spends time sitting at a desk he has in another row with the other employees.

Past the desks at the right far wall is another glass-walled meeting room for smaller team discussions. In the center of the aisle and to the left of the meeting room is the rear exit to the parking lot.

Teams

There are a number of organizational units within Travelco based around the different product lines such as hotel and flights as well as teams focused on mobile and search and a number of non-technical teams. Organizationally, these units are mixed across different teams to create multidisciplinary groups. Employees are more beholden to these teams than they are to their organizational unit since their direct superior is the manager of their team. Since this is still

a smaller company, there are never more than four hierarchical levels between an employee and company executives.

Decisions on teams are not made by the manager alone. For example, I observed managers planning to integrate social functionality into their website and developing a new visual scheme for an online offering. While managers need the support of their superiors, they also have to get informal approval from other managers. This can take a fair amount of time, and decisions at the top to change direction can derail this process and require a manager to start the process all over again. In the case of the social functionality integration, the manager told me that it would only take a few hours to complete the code for the integration. After she decided that she wanted to move forward with this, however, it took four days to talk to all the different managers at Travelco and get approval. This could have happened more quickly, but on the third day one of her superiors told her to change the way that the integration would look, requiring her to talk to the other managers again.

Subgroups

For this study we had broad participation from across the company. However one group of employees from a foreign country almost universally did not participate. This group seemed to be socially isolated from the rest of the company. I noticed that they often spent time together in the kitchen speaking in their native language, and when commenting on this to a Travelco employee her reply was: “Yeah, those crazy [individuals from the foreign country].” Executives at the company also referred to them collectively, and said that there were “difficulties” associated with their isolation.

6.3. Methods

We had multiple levels of data collection for this study so that we could fully instrument all aspects of communication. Participants would wear the Sociometric Badges while that were at work, and initially we set the length of the study to three months, but due to a variety of circumstances this was reduced to six weeks. This remains, however, the longest Sociometric Badge study we have conducted to date.

In addition to the badges, we also collected data on the e-mail communication of participants. We did not collect information on the contents of the e-mails, although we did collect information on the e-mail headers (i.e. to, from, cc, subject, date, etc.). E-mail addresses that did not belong to study participants were hashed for anonymization purposes.

Subjects also answered daily surveys on the web about their day. These questions were based on those that we have used in previous studies as well as those used in previous research. We were also able to add or remove questions given events that occurred over the course of the study. Survey question order was also randomized each time a participant answered the survey. The specific questions are listed in Table 11 below.

Question	Answer Type	Source	Notes
I had too much to do at work today.	7-Point Likert Scale	(Spector 1985)	
Did you work from home all day today?	Yes/No		Stopped asking this question at study midpoint
Did you work today?	<ul style="list-style-type: none"> • Yes, from the office • Yes, from home • No 		Started asking this question at study midpoint
Today it was easy getting the information I needed to do my job.	7-Point Likert Scale	Adapted from (Olguin Olguin, Waber, et al. 2009)	
Today	7-Point Likert Scale	Adapted from (Olguin	

communication seemed good within my work group.		Olguin, Waber, et al. 2009)	
I am very satisfied with my job today	7-Point Likert Scale	Adapted from the Hackman-Oldham Job Diagnostic Survey (Hackman and Oldham 1975)	
I feel that I was productive today.	7-Point Likert Scale	Adapted from (Olguin, Waber, et al. 2009)	
Today was not stressful.	7-Point Likert Scale		
I was upset by the reduction in workforce yesterday.	7-Point Likert Scale		Asked only on the day after layoffs

Table 11. Survey Questions for the Travelco Study.

Overall, 72 participants wore the Sociometric Badges, and we received e-mail data and survey information from 41 of those participants.

Travelco also provided us with demographic and corporate information on all of their employees. This included gender, age, tenure at Travelco, manager, and organizational unit. While we initially intended to supplement this information with survey data from a personality inventory as well as a social network roster survey, management at Travelco felt that this would be too much of an imposition on participants.

6.4. Participant Observation

I started this study to understand better how network constraint contributes to performance and job satisfaction. While I would be collecting quantitative behavioral data, I wanted to better understand *why* social support was related to outcomes like job satisfaction and productivity. I hoped that by participating in the everyday life of the office I would gain new perspectives on my experience there.

Method

Concretely, with the participant observation portion of this study I wanted to understand what motivated people to interact, how those interactions impacted them, and why. To do this I had to observe and interact with different groups at Travelco. I was able to get an initial feel of the social structure from Sara and Bill and learned that they regarded Travelco as a “tight-knit group,” but hierarchy and function played a prominent role in the way people would interact (managers, programmers, and support staff). I observed and interacted with people from each of these different functions in different circumstances to get a balanced look at the underlying dynamics of the organization.

I structured my participant observation into two separate but interdependent phases. First, I observed interactions taking place in different locations in the office at different times and dates. This allowed me to verify interaction data from the Sociometric Badges as well as begin to hypothesize about some of the norms of interaction within Travelco. This phase was mostly concentrated in the first three weeks of the study.

The second phase was centered on having extended conversations with employees from across the company. I was given a desk at Travelco in the main work area and hallway and became involved in a number of informal gatherings.

Observational Method

After spending a few days at Travelco, it became apparent to me that the kitchen was the locus of interaction activity. This then became an ideal place for me to sit and observe interactions unobtrusively as well as join in these conversations when appropriate. I spent a total of two weeks collecting observational data in the kitchen.

Over the next six weeks I spent much more time collecting observational data from my desk, which was located right on the main hallway. It became apparent that while the kitchen

was the center of the social world, the vast majority of interactions were occurring in the office. Interestingly, since desks were more private locations than the kitchen, this is where a lot of gossip about happenings within the company would take place, and this would prove invaluable in my analysis.

Interaction Method

While I would approach people to conduct informal interviews about different events occurring at Travelco, most of the time I interacted with people in unstructured discussions. During my time observing people in the kitchen, I would eat lunch with different groups in the kitchen each day. This allowed me to hear their conversations with each other as well as probe a little deeper when interesting topics came up.

I participated in conversations more when the topic revolved around interpersonal relationships, morale, and productivity, as I believed that these subjects were central to my goal of understanding the relationship between network constraint and outcomes. Except in the case of workforce reduction, which I discuss below, I did not broach these topics myself, but rather waited during observation to see if one of these topics was being discussed, at which point I would try to join the conversation. I would also engage people in idle chat as people came into the office or were leaving for the day. If an interesting topic came up, I would press them for more detail and their perspective.

While a significant percentage of people ate lunch in the kitchen, others went to the cafeteria located in the building or out to restaurants. I joined people there as well to sample a different demographic, although there was some overlap in the groups. Because more people could sit at a table in the cafeteria, lunch groups tended to be larger.

Every week I had to collect badges to download data, and this provided a perfect opportunity to engage with participants. This helped me see what events were on the horizon as well as understand what the different teams at Travelco were up to.

6.5. Results

To understand the relationship between network constraint and outcomes, I wanted to catalogue the kinds of interactions that seemed to me to most contribute to network constraint. I looked for interactions that seemed to generate high levels of social support or camaraderie. If network constraint emerges more from social group interactions, that would imply a different course of action than if work related one-on-one conversations were the biggest contributor. Given the results of the call center study, I hypothesized that informal interactions (interactions that do not occur at formal meetings or with the goal of completing a work-related requirement) are major contributors to network constraint and its positive effects.

I catalogued the various kinds of interactions along the axes of group size and function (social vs. work-related) in Table 12. Below I discuss the effects of each type of interaction in terms of qualitative, quantitative, and behavioral impact.

In the Travelco study, I used a prototype of a new Sociometric Badge that did not provide location information. However, we were still able to recognize group interactions using IR data. Although this is not as precise as our previous work that used the radio, our results do fit nicely with our observational data. Out of the 41160 interaction events detected, dyads made up 89%, small groups made up 10%, and large groups made up the remaining 1%. Large groups were essentially quickly shifting small groups, where at any one instant people were talking to only a few others. These groups would change so quickly, however, that they were fundamentally different from small group interactions.

Group Size \ Sociality	Social	Work Related
Dyad	Chat at the coffee machine	Implementation discussion
Small Group (3 – 5 People)	Beer 30 conversation	Team meeting
Large Group (>5 People)	Lunch in the cafeteria	Company-wide meeting

Table 12. Types of Interactions and Examples.

Overall Results

Table 13 we shows summary statistics of the badge and e-mail data, and Table 14 shows the correlational results.

Variable	Mean	Std. Dev	Shapiro-Wilk's Statistic
1. Workload	4.26	1.13	0.97
2. Information Adequacy	5.27	1.17	0.97
3. Team Communication	5.41	0.54	0.97
4. Job Satisfaction	5.42	0.63	0.98
5. Productivity	5.44	0.54	0.97
6. Stress	3.56	0.74	0.98
7. Upset by Layoff	4.94	1.30	0.92
8. E-Mail Network Constraint	0.53	0.15	0.94
9. E-Mail Betweenness ⁴	1.47	1.47	0.80***
10. E-Mail Responsiveness	11.35	7.92	0.85***
11. Total E-Mails ⁴	354.62	349.16	0.76***

⁴ The log of these features is normally distributed (Shapiro-Wilk's Statistic = 0.97). Results reported below remain unchanged if we use these features, so we use the original feature for ease of interpretation.

12. F2F Network	0.50	0.23	0.87***
Constraint			
13. F2F Betweenness ⁴	2.20	3.00	0.71***
14. IR Contribution	-0.25	0.40	0.94
Index			

Table 13. Summary statistics. E-mail responsiveness is in seconds. $N = 41$, two-tailed test. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	1.00	0.06	0.07	-0.11	-0.13	0.54	0.07	0.00	0.37	0.13	0.23	-0.23	0.06	-0.04
2	0.06	1.00	0.90	0.62	0.52	0.06	-0.04	-0.28	-0.12	-0.11	0.09	0.00	-0.07	0.14
3	0.07	0.90	1.00	0.70	0.59	-0.07	0.01	-0.32	-0.09	-0.19	0.01	0.14	-0.09	0.17
4	-0.11	0.62	0.70	1.00	0.85	-0.20	0.08	-0.19	-0.16	-0.31	0.04	0.24	-0.13	0.07
5	-0.13	0.52	0.59	0.85	1.00	-0.20	0.05	-0.11	0.01	-0.19	0.16	0.32	-0.10	0.01
6	0.54	0.06	-0.07	-0.20	-0.20	1.00	0.30	-0.08	0.18	0.22	0.19	-0.35	0.18	-0.10
7	0.07	-0.04	0.01	0.08	0.05	0.30	1.00	0.16	0.03	-0.09	-0.06	-0.11	0.22	-0.22
8	0.00	-0.28	-0.32	-0.19	-0.11	-0.08	0.16	1.00	0.15	0.23	0.07	0.15	0.01	-0.23
9	0.37	-0.12	-0.09	-0.16	0.01	0.18	0.03	0.15	1.00	0.36	0.65	0.08	-0.02	-0.08
10	0.13	-0.11	-0.19	-0.31	-0.19	0.22	-0.09	0.23	0.36	1.00	0.07	-0.15	0.35	-0.29
11	0.23	0.09	0.01	0.04	0.16	0.19	-0.06	0.07	0.65	0.07	1.00	0.08	-0.13	-0.01
12	-0.23	0.00	0.14	0.24	0.32	-0.35	-0.11	0.15	0.08	-0.15	0.08	1.00	-0.57	0.38
13	0.06	-0.07	-0.09	-0.13	-0.10	0.18	0.22	0.01	-0.02	0.35	-0.13	-0.57	1.00	-0.64
14	-0.04	0.14	0.17	0.07	0.01	-0.10	-0.22	-0.23	-0.08	-0.29	-0.01	0.38	-0.64	1.00

Table 14. Correlational results. $N = 41$, two-tailed test. $p < 0.05$, $p < 0.0001$.

Our results are consistent with those we observed in our previous studies, particularly face-to-face network constraint's positive relationship to self-reported job satisfaction and productivity and its negative relationship to reported stress, although not all of these relationships are significant.

Similar to the Germany study discussed in Chapter 4, we also split the data into two segments to observe changes in behaviors over time. We only consider the 31 individuals who

participated for at least a week in both segments. These results are shown below in Tables 15 and 16.

Variable	Mean	Std. Dev	Shapiro-Wilk's Statistic
1. Workload	0.22	0.53	0.96
2. Information Adequacy	-0.22	0.79	0.98
3. Team Communication	-0.22	0.69	0.97
4. Job Satisfaction	-0.32	0.66	0.95
5. Productivity	-0.43	0.68	0.98
6. Stress	0.22	1.03	0.94
8. E-Mail Network Constraint	0.00	0.12	0.95
9. E-Mail Betweenness	0.00	0.02	0.91*
10. E-Mail Responsiveness	-4765.00	61145.11	0.71***
11. Total E-Mails	23.19	89.80	0.96
12. F2F Network Constraint	0.11	0.25	0.91*
13. F2F Betweenness	0.01	0.05	0.88**

Table 15. Summary difference statistics. E-mail responsiveness is in seconds. $N = 31$, two-tailed test. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

Variable	1	2	3	4	5	6	8	9	10	11	12	13
1	1.00	0.04	0.13	-0.03	-0.04	0.22	-0.11	0.16	-0.24	0.09	-0.14	0.24
2	0.04	1.00	0.85	0.48	0.48	-0.24	-0.11	-0.24	0.08	0.29	-0.40	-0.06
3	0.13	0.85	1.00	0.57	0.58	-0.17	-0.14	0.02	-0.06	0.23	-0.44	0.08
4	-0.03	0.48	0.57	1.00	0.68	-0.36	-0.11	-0.03	0.05	-0.13	-0.27	-0.11
5	-0.04	0.48	0.58	0.68	1.00	-0.26	-0.20	-0.16	0.11	0.01	-0.04	-0.01
6	0.22	-0.24	-0.17	-0.36	-0.26	1.00	-0.14	0.27	0.05	0.25	0.13	-0.13
8	-0.11	-0.11	-0.14	-0.11	-0.20	-0.14	1.00	-0.22	0.04	0.32	-0.06	0.07
9	0.16	-0.24	0.02	-0.03	-0.16	0.27	-0.22	1.00	-0.28	-0.02	0.09	0.03
10	-0.24	0.08	-0.06	0.05	0.11	0.05	0.04	-0.28	1.00	-0.08	0.15	-0.22

11	0.09	0.29	0.23	-0.13	0.01	0.25	0.32	-0.02	-0.08	1.00	-0.23	0.00
12	-0.14	-0.40	-0.44	-0.27	-0.04	0.13	-0.06	0.09	0.15	-0.23	1.00	-0.44
13	0.24	-0.06	0.08	-0.11	-0.01	-0.13	0.07	0.03	-0.22	0.00	-0.44	1.00

Table 16. Panel difference correlation results. $N = 31$, two-tailed test. $p < 0.05$, $p < 0.01$.

Below I describe my observations of events and activity at Travelco in more detail, but this data was split on the day of a workforce reduction event (coincidentally this occurred at the exact midpoint of the study). This event drastically changed the mood of many people at the office, and our quantitative and behavioral data picks up on these changes. Notably there was increased workload, decreased information adequacy, decreased team communication, decreased job satisfaction, decreased productivity, and increased stress.

We observed almost no change in e-mail communication patterns. This is consistent with our belief that e-mail communication reflects formal team and organizational communication and does not capture the informal processes within organizations. Face-to-face communication patterns, however, did change.

Network constraint significantly increased ($p = 0.02$), and this change was correlated with a drop in information adequacy and team communication. This was due to groups becoming more cohesive in the wake of the layoffs. People who were more troubled by the layoffs tended to form tighter groups ($r = -0.11$, n.s.). In addition, when we controlled for survey response on the layoff question the negative correlation with information adequacy and team communication change disappeared, indicating that the cause of the decrease in information adequacy and team communication was layoffs and not an increase in network constraint.

One of my more meaningful observations was that the number of people joined in a conversation was associated strongly with the subject of the interaction.

Dyadic Interactions

What I first noticed at Travelco was that one-on-one interactions were overwhelmingly work related, with only three out of 32 dyadic interactions that I observed in their entirety focused explicitly on social topics. During the course of the day people would often go their co-worker's desk to ask about implementation details of some new website functionality that they were working on, and in the office setting this comprised the majority of interactions that I observed. The three exceptions to this occurred in the kitchen and by the foosball table, which are the more informal areas of the office.

Social

The social dyadic interactions I observed occurred through chance meetings in the informal areas of the office, and did not represent a deliberate attempt to speak with a person. I observed 140 short interactions (less than one minute) that occurred as people were walking by each other, but I was not able to confirm the content of these conversations since they lasted less than one minute. For five of these conversations I was able to later ask one of the participants about the content of those brief encounters, and they told me that it was "just talking about how [person's name] was doing." Given the short nature of the discussions and similar body cues, it's likely that these interactions were mainly social in nature.

One particular example of this was two participants speaking about their vacation plans by the coffee machine. They were both standing around not looking at one another while their drinks were being made. But they soon started to talk about their upcoming vacation plans since they were both going away the next week. These two people said that they did not know each other very well since they were on completely different teams and were separated by 15 years in age. What started as an awkward conversation became more engaged and lively. They both

walked away from the interaction walking noticeably more quickly, in a way that seemed to me to be energetic.

Work Related

Of the one-on-one conversations that I was able to observe and collect content information on, 91% were work related interactions. These interactions appeared to be intentional, with a co-worker walking over to another person's desk to talk. This makes these interactions difficult to behaviorally distinguish from social interactions, as they look exactly the same from a sensor's point of view.

However the effect of these interactions was much different than the social conversations that I observed. While participants in a social conversation appeared to have a bounce in their step, I didn't detect any noticeable change in walking patterns or other outward social signals after work related interactions. Of the conversations I observed, work related interactions took on average 14 minutes, versus the average length of 3 minutes for social interactions. Admittedly, I was not able to observe many social dyadic interactions, however since it seems that short interactions that occurred in the hallways were mainly social this may be an overestimate of the length of dyadic social interactions. This implies that work related interactions may contribute to network constraint more than social dyadic interactions.

An example involves two employees talking about "adding social functionality to the website." One worker came over to the other's desk to ask how other sites "had gone about incorporating similar functionality." Together they identified the "pros and cons of the different possible approaches." This discussion appeared to be fairly technical in nature. Another person wandering by who started to listen in quickly walked away, and as he left he said, in effect, "I don't know what they're talking about."

Implications and Behavioral Data

The implication of all of this is that the dyadic interactions that contribute most to network constraint are work related since they seem to last more than four times as long as social interactions and may be more frequent, but these interactions did not seem to contribute much to social support. That is not to say that relationships are only social or only work related. I saw that nearly all relationships at Travelco had both a social and work related component. Given the change in behavior that I observed after social interactions, however, it would appear that the social component of these ties was clearly more related to the job satisfaction outcome. It is unclear from this data whether this would also contribute to increased productivity directly.

Strong work related ties would most likely be indicative of increased productivity, but it was hard to directly infer that from the data I collected. I noticed that intense, work-related interactions seemed to clear up misunderstandings for both people involved, and that is borne out in the badge data when we examine the strength of dyadic ties.

We felt that the best way to measure the effect of dyadic interactions was to examine the social network considering only dyadic interactions, since this allows us to isolate their effects. We found that network constraint in the dyad network was the lowest of all interaction types ($\mu = 0.52$, significantly lower than large group network constraint ($p < 0.0001$)). We also found similar results when we removed dyadic interactions from the overall social network. This is encouraging, since it indicates that network constraint is a viable measure for social support. As we discuss next, small and large groups were much more conducive to creating networks high in constraint and social support.

Small Group Interactions

While at Travelco I was intrigued by the small groups of people that would join up and dissipate. Two people would start talking together by their desks, and then someone walking by or in the area would jump in. Out of the 21 small group interactions that I observed, 17 were social, with the rest representing team meetings that I attended.

Social

Serendipitous groups that formed in the office were by far the most common small group interactions (12 out of 21). They were also the shortest interactions, lasting on average 9 minutes versus 32 minutes for other small group interactions. People would talk about non-work related topics such as video games or current events. If a work-related topic did come up, however, it would normally fissure the group into one-on-one interactions around what I took to be technical expertise.

I saw one interaction in particular where the conversation was originally about music genres. When the topic wandered to website organization and layout, however, one of the participants politely excused himself and went back to his desk. We saw behavior similar to this in the dyadic interaction example on social functionality that was mentioned above, however that interaction started as a two person conversation and the third individual never actually participated in the discussion.

Lunch groups were also a common source of small group interactions. Small groups of three or four people would often eat lunch together in the kitchen. Some of these groups remained stable over the course of the six week study but most changed day to day. Lunch groups would normally form by two or three people heading down the main walkway and a few other people jumping up to join them. However, most lunch groups would end up becoming

large group interactions, since the majority of people ate in the cafeteria or went out to lunch in groups of 7 or 8.

Small groups also formed around specific activities. Beer 30 would bring together small groups of people that normally didn't talk to each other as seen in the badge data (we discuss Beer 30 in more detail below). The gym on the first floor conducted yoga classes a few times a week, and there was a regular group of employees who would go to this class together. About half of all employees would exercise in the gym once a week, and aside from the yoga group they would normally exercise individually. The yoga group seemed to be tight-knit. Participants told me that they did not know each other well before they started taking the class together, but over time they had become quite close.

These close groups were particularly important in stressful periods. The day after layoffs were announced there was a marked increase in small and large group interactions, and although I was not able to collect content information on all of them I observed 14 small group interactions occurring around the office that day. These appeared to be mostly close friends speaking to each other. One group was talking about how surprised they were by the announcement, while another group was talking about how "ruthlessly driven by efficiency" the company was. One of the employees told me that these group interactions "[were] really helpful, in easing [our] stress," and since all discussions that I heard that day centered on the layoffs, it seemed to me that these interactions were generally important for stress reduction.

Work-Related

Team meetings were also small group interactions, and they had a different tenor and effect than social gatherings. As with dyadic interactions, meetings did not necessarily have a predictable effect on the mood and behavior of participants. Meetings at Travelco had many

purposes, from gathering consensus on a new idea to planning out a development path for a new project.

Meetings could change an individual's workload or even undo some work that they had already completed. Four individuals who had their workload changed at different meetings relayed to me that it was a frustrating experience, although I was not able to attend these meetings. In contrast to this, some meetings elevated an individual's role or got them thinking about a new problem. This would leave participants saying they were energized and excited about new opportunities, which I observed during the four meetings that I attended.

Implications and Behavioral Data

Overall, small groups seem to increase social support more than dyadic interactions. Just like dyadic interactions, however, these small groups had a social focus as well as a work focus. Social interactions were more serendipitous, but they seemed driven by pre-existing social ties. Team meetings accounted for a minority of small group interactions, but since these group interactions were repeated they likely also contributed to network constraint.

When we examined the social network using only small group interactions we found that network constraint was higher than in the dyadic network ($\mu = 0.61$), although this was not a significant difference. This is not surprising since these interactions were longer on average and also included more people. It was significantly lower than large group network constraint, however ($p < 0.0001$). We obtained similar results when we removed small group interactions from the overall social network, as this had lower network constraint than when we removed dyadic interactions but higher network constraint than when we removed large group interactions.

Large Groups

Large group interactions, those with more than 5 participants, did not occur nearly as frequently as dyadic and small group interactions, making up only 1% of the total number of interaction instances. However since these interactions incorporated so many people and lasted for much longer than small group interactions, they were a key contributor to social support. They were also easier for me to observe, since they occurred mostly at lunch and in publicized all-hands meetings for the entire company. Overall I observed 19 large group interactions, of which only two were all-hands meetings.

Social

Most large group interactions were social events. While lunch groups in the kitchen normally had no more than 4 people, lunch groups in the cafeteria could easily have 10 to 15 people. These large groups would form rather organically. One day I went down to the cafeteria with two employees from Travelco, and once we sat down at a table other employees from Travelco naturally gravitated there, until in a few minutes we had filled up the entire table. At first we started talking as a table, and then we slowly broke off into small groups. When someone brought up a current event topic that everyone was interested in, though, small group conversations quickly stopped and the entire table began talking again. The people who were interacting together changed quite frequently, so that while two people may speak to each other for a few minutes, they would quickly shift to other people sitting close to them at the table.

These interactions were incredibly energetic, and afterwards when we would walk back up to the office I would find myself talking with different people than I had on the way down. These interactions gave everyone a sense of community, and since these lunch groups had relatively constant members it allowed for the cohesion of the group to increase. There were

actually two of these lunch groups at Travelco, and although there was some cross-pollination hierarchical and tenure differences mostly kept the groups apart.

Work-Related

Work related large group interactions consisted entirely of all-hands meetings or meetings between multiple teams. These were not so much interactions as they were presentations with brief discussion periods. In fact, the badges only recognized a few of these meetings since there is often not enough communication for detection.

These meetings were often of broad importance, as one was held when I first went to Travelco to pitch the study to the employees. Another was held following the layoffs. For these meetings it appeared that the interactions afterward were most important since that was where people discussed their thoughts on the meeting with their peers. Overall, these formal meetings comprised a small fraction of large group meetings since they were relatively infrequent compared to lunch gatherings.

Implications and Behavioral Data

Large group interactions appear to be one of the large contributors to social support and network constraint. Formal large group meetings were rare, and the near daily lunch meetings seemed to engender a sense of community and trust across the company in terms of enabling later interaction. As measured by the Sociometric Badges, people who interacted with each other in large groups were 36% more likely to interact in dyads ($p < 0.0001$). In raw numbers lunch time interactions were infrequent (approximately 40 as detected by the badges over the length of the study), but since they lasted nearly an hour (53 minutes on average) and had so many participants they were an indispensable part of the social fabric of the company.

When we looked at the social network using only large group interactions we found that network constraint is higher than in both the dyadic and small group networks ($\mu = 0.93$, $p < 0.0001$). We obtained similar results when we removed large group interactions from the overall social network, as this had the lowest network constraint of any network we examined.

When comparing the effects of these networks, we saw that an individual's amount of large group interaction was correlated with an increased resistance to the effects of layoffs ($r = -0.33$). Dyadic interactions, on the other hand, had the opposite effect, ($r = 0.33$), although neither of these effects were significant. This implies that larger, cohesive interactions are the most effective mechanism for increasing network constraint and social support. Since large group interactions also increase later dyadic interaction, we can infer that networks high in constraint provide structure for tacit knowledge exchange (information clearing). This helps explain our results in the call center study. There we had 20 people take a break at the same time, and they would mostly go have coffee together. This sort of engineered large group interaction would help contribute to increased network constraint and by extension reduced stress (as we saw with the reduced effect of layoffs), and it would also lead to tacit knowledge exchange and later to increased performance.

What seems to be important about these larger group interactions is that they give participants a broader view of the social context. In dyadic or small group conversation with others the focus is much narrower, typically on a particular topic or work problem. In larger groups everyone's perspective is broadened, and we speculate that this can lead to information seeking later as one has a better idea about the knowledge of other people in the group. However large group interactions can have unexpected effects as the following describes.

Beer 30

Travelco's management said that they were very focused on promoting a "welcoming workplace" and a "strong culture." One of the most visible aspects of that effort was "Beer 30." Beer 30 happened once a week, on Friday at 4:30 PM until around 5:15 PM. Not surprisingly, beer is served at this event, which is held in the kitchen, hence the moniker "Beer 30."

Beer 30 was viewed as a major event at Travelco and was something that many looked forward to. It appealed mostly to the younger crowd, and older employees generally didn't participate or only came for a few minutes. In addition to beer other food and drinks were available. A party atmosphere prevailed.

Beer 30 seemed mainly to allow participants an opportunity to "catch up" with people that they normally didn't get a chance to talk to during the week. While it's always possible to go over to someone's desk and talk or take them out to lunch, most of the interactions at Beer 30 were between people who seemed to me to not be quite at that level of acquaintance. I was involved in conversations about someone buying a new car, an event at their child's school, and countless interactions about weekend plans.

As a consequence, these conversations were more "chit-chat" than engaging discussions of "serious topics." I felt that while people smiled and seemed to me to have a good time at the event, it did not promote important interactions. When I discussed this with a senior employee, he told me that he went to Beer 30 when he didn't have much to do. But he said it was "mostly a waste of time."

To study the effect of Beer 30, we compared the volume of communication that occurred during Beer 30 to the volume of communication that occurred at that same time on other days of the week. The results are shown below in Figure 7.

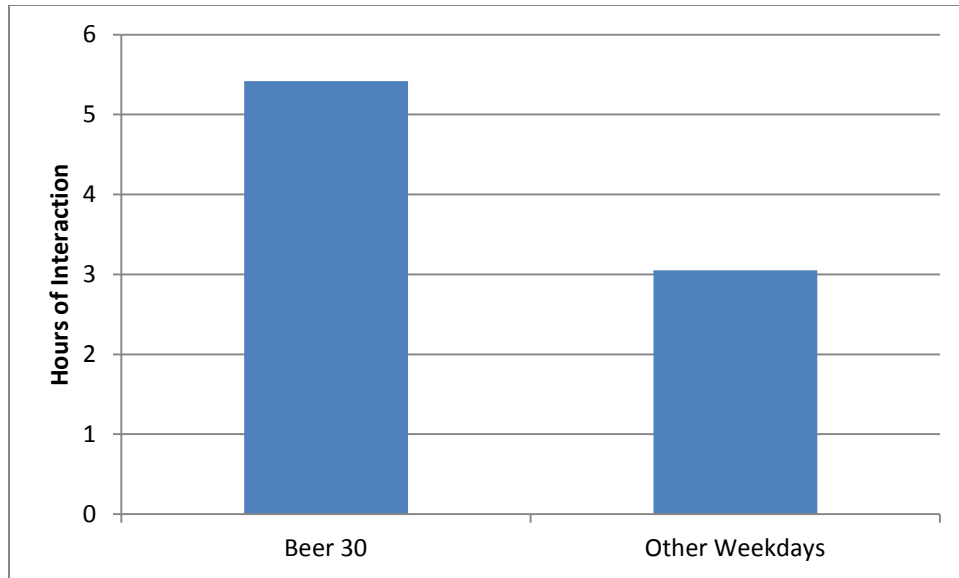


Figure 7. Average Amount of Interaction During Beer 30 vs. Other Days of the Week.

As can be seen from the figure, Beer 30 nearly doubles the amount of interaction that occurs from 4:30 – 5:15. The first five minutes of Beer 30 are the busiest, with about 30 people coming to the kitchen. After people grab a bottle of beer and a quick snack, the kitchen quickly empties out. Throughout the rest of the event there are normally only four to ten people in the kitchen.

We also examined what kind of interactions were occurring at Beer 30. If Beer 30 interactions are removed from the social network, network constraint increased by 17%, although this difference was not significant ($p = 0.1$). Such events may not be conducive for higher network constraint.

This is not to say that this event is counterproductive. Qualitatively, Beer 30 was viewed as positive by most employees. As we saw in the badge data Beer 30 encourages people to speak with people they don't normally talk to, and so perhaps it becomes easier for information to be shared between these people in the future.

Layoffs

I came in to Travelco on a regular Friday, and immediately noticed that something was different. The office was quiet. There were a number of small groups milling about the office. I sat down at my desk and took out my notebook and was approached by one of the employees I knew well.

She told me that a number of people were laid off “due to poor performance and efficiency concerns.” A few people from the local office were gone, as were a number of people from another location. It was announced the day before at a company-wide meeting, and people were upset because, in her words, “it’s a close knit group.”

I approached one of the senior managers and asked about the layoffs, and he said that “from an efficiency perspective [they] have to cut some people.” He also revealed that “Travelco has a culture where they like to cut dead weight to make sure that they’re as efficient as possible.”

I spent much of my time that day talking to employees in different social and formal groups. The three employees I spoke to who had worked at more traditional companies were not bothered by it. They said they didn’t know the people who lost their jobs personally and had seen similar behavior at other companies where they had worked. These people also tended to be socially isolated and not speak with anyone that they did not formally have to speak to.

In contrast, in a private conversation with a long-time employee, he gave me a different view of the situation. “People are supposedly not fired without warning,” he said, although he wasn’t sure if that was true. While he was talking to me he appeared to be worried about people overhearing, and kept glancing over his shoulder. “They’re ruthless,” he told me.

I felt like the life had been sucked out of the office. And when we look at our results from above, this is validated in the behavioral and survey data that we collected. In our panel

data, we saw that job satisfaction decreased, stress increased, productivity dropped, and people rated information adequacy and team communication lower than before the layoffs.

We also saw an increase in network constraint after the layoffs, a dynamic that makes sense when considering the results from the German bank study. There we saw that changes in job satisfaction were strongly correlated with changes in network constraint. But this occurred in a situation where no major exogenous events occurred. In the case of Travelco, increased network constraint and group cohesiveness was perhaps a way for people to try to deal with the layoffs. This was more or less confirmed by the informal interviews that I conducted. In the words of one employee: “It’s been tough, and we just need to lean on each other.”

Chapter 7

Discussion and Future Work

Overall, the four studies that we discussed above lend support to our hypothesis that face-to-face network constraint is associated with important outcomes such as job satisfaction and productivity. We showed at an aggregate level that network constraint correlated positively with both job satisfaction (German bank study) and productivity (Chicago study and call center study). These studies also showed that changes in network constraint over time were positively related to changes in job satisfaction and productivity, strengthening the case for causality. In the call center study, we also showed that by changing break structure we could change network constraint and productivity as well.

While this research provides a quantitative case for network constraint as causally-related to positive outcomes, we still have only theorized about the why. The Travelco study suggests that people band together in times of stress and uncovers new features to look at to help explain our results. In particular, splitting interactions by the size of the group proved to be quite useful and should inform future research using Sociometric Badges. While these initial results from the Travelco study are encouraging, there are many other possible avenues for future investigation.

7.1. Travelco Study

E-Mail Analysis

My focus in the Travelco analysis was on face-to-face. However there are opportunities to use the e-mail data collected at Travelco to examine new and important questions. Using subject lines and times we can speculate what e-mails appear to “cause” face-to-face interactions (e.g. setting up meetings). This builds on top of previous work where we showed that physically

proximate individuals had correlated face-to-face and e-mail patterns (Olguin Olguin, Waber, et al. 2009). Our fine-grained survey data can similarly offer new insights into behavior at Travelco.

Daily Survey Analysis

The daily survey data that we collected at Travelco can also be used to understand the social network in a deeper way. In particular I noticed that talking to different people yielded a predictable affective change in a person's mood. Given that there are positive and negative relationships at work, we can identify these relationships by combing badge and daily survey data. This would involve detecting interactions using the badge and see if these interactions were correlated with daily changes in that individual's job satisfaction or evaluation of group communication.

I did not consider the affective content of ties in this work, but this information is most likely crucial to understanding how networks function. We would expect that a high constraint network also high in positive ties would be positive, but as more negative ties are introduced this effect would gradually decrease. These positive and negative ties would also come into play when examining events such as layoffs, mergers, stock run-ups, etc.

Layoff Analysis

Our first look at layoffs showed that there was an overall decrease in all examined outcomes. This was coupled with an increase in face-to-face network constraint. Not surprisingly, this analysis could benefit from some additional social context. In particular, we knew who spoke to the people who got laid off, and this likely influenced the response of employees. Essentially this would reveal how people are affected by layoffs when they know the people who were let go. In early analysis we have seen that those who indicated on our survey

that they were more effected by the layoffs reacted strongly to many other events over the course of the study.

Since only half of our study participants answered the question about the layoffs, it is important to discover if the pattern holds across all participants. This could suggest interventions that might ease the stress for those most affected by layoffs, since we can see how they reacted to events such as Beer 30. Financial support could be provided by the company for private lunch sessions to increase the network constraint of these individuals or rearranging desks so that people sit closer to others that they normally talk to.

While these opportunities are by no means exhaustive, they do illustrate the potential of this rich data set. It is instructive, however, to see how these opportunities fit into a larger framework that is enabled by the Sociometric Badges. This will be useful to management researchers as it will help identify new areas of inquiry that the badge enables.

7.2. Future Opportunities

In this thesis I studied how social support is related to certain specified outcomes using the Sociometric Badge. This technology allowed me to observe interactions in new ways. For management research this opens up new opportunities. In this section, I look at promising new areas of inquiry and detail how these opportunities could help further the study of important topics in management research. I focus particularly on information systems (IS).

Broad Research Opportunities Enabled by Sociometric Badges

Observing Fine Grained Interactions at Low Cost

To understand what new research avenues are opened by the Sociometric Badge, it is instructive to create a taxonomy of the granularity of management research on face-to-face interaction along two different axes: the unit of observation and the timescale of observation.

Table 17 describes how different methods of observation provide data at different granularities in terms of the unit of observation and the time scale on which these units can be observed. I assume that a significant number of different units (noted in parentheses) must be observed at the same time in a real world setting. Timescale refers to both the frequency of coding and the length of the study. It is also important to consider the relative costs and restrictions of these different techniques, which we detail in Table 18.

Observational Unit Timescale	Seconds	Minutes	Hours	Days	Months	Years
	Individuals (30)	V	V, H	E, H	E, H, S	E, H, S
Dyads (30)	X	X	X	S	S	S
Teams (10)	V	V	H	H, S	S	S
Divisions (5)	X	X	X	X	S	S

Table 17. Time Scales of Data Collection Across Traditional Methods. E = Experience Sampling, H = Human Observation, S = Survey, V = Video.

Technique Accuracy	Coding Accuracy	Coding Frequency	Coding Granularity	Space/Time Restrictions	Cost/Difficulty
Surveys	Low	Low	High	High	Low
Experience Sampling	Low	Low	Low	Medium	Medium
Human Observers	Low	Medium	Low	High	High
Video	High	High	High	High	Very High
Sociometric Badges	Very High	Very High	Very High	Low	Low/Medium

Table 18. Relative Costs, Benefits and Constraints of Different Data Collection Methods.

For example, Table 18 shows that although video can technically collect granular data on individuals and teams, it is often prohibitively expensive and challenging to deploy video recorders in natural settings. Similarly, surveys impose heavy time restrictions on researchers in terms of how often they can be conducted on the same population, since fine-grained surveys are difficult to repeat on a daily or even monthly basis.

From this table it is apparent that Sociometric Badges offer some of the advantages of video coding but at substantially lower cost and with very low space and time restrictions. These advantages are similar to those provided by electronic communication data, although the granularity of electronic communication is lower since there is no data on people when not using

a computer. Therefore we would expect Sociometric Badges to enable for the physical world what electronic communication data collection enables for the virtual world: fine-grained longitudinal studies of human interaction and behavior.

Surveys allow researchers to collect data on human interaction and behavior for longer periods of time than human observation, but human observation is necessary for fine grained data collection. The difficulties encountered when trying to observe human behavior a) for long time periods, b) at very fine granularity and c) in the physical realm, offer three classes of opportunities for the Sociometric Badge to move IS and management research forward: 1) Thin Slice Behavioral Dynamics, 2) Fine-Grained Longitudinal Studies, and 3) Informal Interaction Analysis. I discuss each of these opportunities in detail in the next three sections.

Analyzing “Thin Slice” Behavioral Dynamics

Thin slices of behavior are typically the purview of laboratory studies. These studies show participants very short audio or video clips of another person, often lasting less than one minute, and then ask them to make judgments based on that “thin slice” (Ambady and Rosenthal 1992). Such evaluations are often remarkably accurate, and are offered as evidence that our quick decision making mechanisms are more accurate than our cognitive mechanisms. Some examples include students rating professors based on a short clip of one of their lectures (Ambady and Rosenthal 1993) and participants gauging the intelligence and personality of another person based on thin slices of observation (Borkenau, et al. 2004).

More recently it has been shown that computers can attend to these thin slice signals as well. Curhan and Pentland (2007) showed that a computer could accurately predict negotiation outcomes by examining the speaking style of the participants during the first five minutes. In their work, activity level, conversational engagement, prosodic emphasis, and vocal mirroring

predicted 30% of the variance in outcomes. These findings have been replicated in small group studies (Jayagopi, et al. 2008), suggesting that this is not just an individual or dyadic phenomenon, but one which extends across a wide range of group sizes.

Until now this research has been confined to the laboratory, since audio and video recording in a corporate environment is difficult. Sociometric Badges, however, allow us to study these same fine grained phenomena in real organizations across longer periods of time. This leads to a number of new potential research avenues.

Studies of systematic bias in manager-employee relations may benefit from a “thin slices” approach. For example, leadership ability in terms of speaking and interaction patterns could be gauged by examining thin slice behavioral data. Leadership is an ephemeral quality that is often ascribed to content-oriented characteristics, such as vision and message. But it is also likely that the mode of delivery of those messages plays a pivotal role in other’s acceptance of that person as a leader. Thin slices research has shown the power of small changes in behavior, changes that are often difficult for humans to consciously observe. When a person is asked why they made a decision based on thin slices data, it is often difficult for them to articulate their reasoning (Ambady and Rosenthal 1993). Behavioral data could put hard numbers behind previously qualitative metrics by showing how interactions with a leader changed a person’s behavior or by identifying changes in the substance or style of meetings that occurred when a leader spoke up. Concretely, one could look at how a leader changes how much other people speak as well as how engaged people become in these meetings by examining speaking speed and volume modulation changes.

Performance evaluations of employees are similar. The depth of interaction data provided by Sociometric Badges could perhaps uncover systematic biases in manager ratings

depending on behavioral patterns. It would not be surprising, for instance, that if an employee did not closely mirror the speaking style of their manager their performance evaluation would also be lower.

This research could potentially lead us to consider new management techniques. Real time feedback from the Sociometric Badge and electronic information sources could change the dynamics of meetings and provide individuals with a new understanding of how their behavior affects those around them. Kim and her colleagues have already begun developing systems to this effect (Kim, et al. 2008). Their system, called the “Meeting Mediator,” shows groups how they are interacting in real time using Sociometric Badges to stream behavioral data to cell phone displays. By showing the balance of participation and the interaction style of all participants, the authors showed in a laboratory setting that participants drastically changed the dynamics of meetings and engendered greater levels of trust when using Sociometric feedback, particularly when they were geographically distributed. These feedback systems could alter management practice, which is typically concerned with delivering feedback and interventions at a distinct time period. Real time feedback would create a dynamically changing feedback environment, where interventions can occur daily to warn participants about a counter-productive behavior or to change the dynamics of certain interactions when necessary.

Conducting Fine-Grained Longitudinal Studies

Longitudinal studies using surveys or human observation are difficult and have a number of limitations. Longitudinal surveys have low response rates, which reduces the usable sample over time. Additionally with extensive surveys such as leadership 360 degree assessments or in depth surveys on organizational issues respondents cannot be surveyed repeatedly without experiencing fatigue, so researchers typically only collect a few observations for each individual

over many years. Clearly much is changing between each survey, but it is nearly impossible to capture these dynamics with a single data point. Human observation can also be used to collect longitudinal data, but while observation may help explain how organizational culture changes over time, a single individual cannot typically provide simultaneous data on the workings of an entire group without sacrificing data granularity.

Fine-grained data collected by badges presents an opportunity to overcome these limitations. For example, a current topic of debate is how social networks form. There has not been a longitudinal study that examines behavior that leads to tie formation in networks. Who do new employees tend to talk to? People they sit close to, people with an outgoing personality, or some combination of the two? And how do these networks change over time? What are the causal factors that underlie these changes? Using Sociometric Badges to conduct long term studies in organizations when new employees are introduced, researchers may be able to answer these questions.

The precise mechanisms of organizational change are also difficult to quantify. While changing formal reporting relationships may change how some information flows, does it really change who talks to whom? When leaders generate change, their impact is often observed at the level of the group, but it is perhaps more important to examine their impact on the behavior of their individual subordinates. Badge research may uncover previously unknown leadership styles and provide guidance for leaders who want to mold a particular kind of organization.

There has also recently been renewed interest in the effect of office layout on group interaction and performance, with researchers observing strong relationships between electronic communication patterns and office layout (Liu 2010). While there has been anecdotal evidence

that these patterns extend to face-to-face communication (W. E. Baker 2000), this remains to be confirmed using electronically recorded micro-behavioral data.

Observing Informal Interaction

Social network research has hinted at the potential importance of informal interaction. Studies in this area have shown that who interacts with whom matters above and beyond the formal structure of organizations and teams (Burt 1992). Traditionally this research has been conducted using surveys, but recently researchers have looked at electronic communication to understand the fine grained dynamics underlying these patterns.

Combining electronic and face-to-face communication using Sociometric Badges could provide a different view of workplace interactions. One of the strengths of these methodologies is observing relationships over long periods of time at fine levels of granularity. There are lingering questions in the management literature regarding the relationship between electronic and face-to-face communication, and as we showed above in Section 4.3, this relationship is not straightforward.

Beyond the relationships between communication media, it is important to understand how events influence communication patterns and vice versa. Effects of promotions and bonuses are often analyzed at the individual level. Companies should promote talented individuals who can become good leaders and should reward high performers. However the social context surrounding these decisions needs further examination. If an individual was a socially central team member but then gets promoted, how does that affect team dynamics and performance? While this has been studied in the laboratory (e.g. (Leavitt 1951)), it has been difficult to determine if these patterns extend to the real world over long periods of time. Sociometric

Badges would allow researchers to pinpoint the exact moment changes occurred across dozens or hundreds of teams and see how it affected the network immediately afterward.

At an even simpler level, one-time events such as office parties and volunteer days could be examined in detail, as we saw in the Travelco study. While these events are often viewed solely in the context of improving morale and giving back to the community, it is also likely that they change the dynamics of some relationships. As we saw in our examination of Travelco and their weekly “Beer 30,” events of this kind can have important and unexpected results.

These events may build social capital, but are there ways to more subtly create social connections by engineering serendipity? As we showed above in our study of a bank’s call center, even a small change to a process as banal as break structure can have far-reaching effects. While break scheduling is sometimes an afterthought, this study showed that decisions such as these can have implications both for performance and perhaps mental health.

Physical health in the workplace can also be studied more easily with Sociometric Badges. Corporate responses to illness are currently ad-hoc and subjective and have little basis in data on how disease actually spreads at work. Some businesses emphasize a “tough-it-out” approach, implicitly encouraging employees to remain at work while they are sick. Other companies send people home at the first symptom of illness and force them to stay home long after any symptoms remain. In work with epidemiologists we constructed a curve trading off productivity with epidemic potential (Waber, Pollock, et al. 2011). This is advantageous because it allows companies to decide appropriate responses based on the organizational context of a disease outbreak (e.g. project deadline coming up, particularly infectious disease spreading in the office, etc.). Using the Sociometric Badges we were able to measure the impact of social factors, such as interaction diversity and density, on disease spread and productivity. We also proposed

new organizational responses to diseases that take into account behavioral patterns associated with a more virulent disease spread. For example, we discussed changing assigned desks and offices for brief periods during outbreaks, as well as organizing “meeting days” to reduce short interactions which were a main cause of disease propagation. Connecting research to action is an important step, and one that is explicitly enabled by Sociometric Badges.

Creating Feedback Systems

Sociometric Badge technology not only enables us to ask new research questions, but also to rethink the way organizations are managed. Real-time sensor data enables real-time feedback on behavior. For example, employees in many organizations are trained for at most a few days before being sent into the organization and asked to perform. By aggregating data from other employees in the organization, we can help people benchmark their progress against the most experienced employees or the most productive employees and give them suggestions about behavioral changes that will aid their development continuously and in real time.

Badge analyses can also aid physical office design and layout strategies. We have found (following seminal work by (Allen 1977)) that the distance between people’s desks is correlated with the probability of their interaction. Quantitatively assigning seats based on this data could be useful when managers want to foster collaboration or limit interaction between specific teams. Office features such as partitions and windows also play a role. Partitions may block the view of different groups from each other. Although open office plans have become more popular, they may not always be the best option as these layouts make interruptions more likely and lead to communication overload (Olguin Olguin, Waber, et al. 2009). Sociometric Badges can be used to test the degree to which patterns of interaction and interruption are affected by changes in

physical office layouts, making management of the physical environments in which work is conducted more conducive to collaboration, cooperation, or individual productivity.

Research Agenda: Specific Applications to Exemplar Topics in Information Systems

In the management research community, the area of Information Systems is poised to take advantage of this new technology. Information Systems scholarship is concerned with evaluating the impact of technology in the workplace and on the connection between technology and the behaviors of the people that use it. IS research has pioneered our understanding of the virtual world and human behavior using electronic data. But current IS research also focuses on areas where electronic information is not available. The majority of research on knowledge sharing, for example, uses surveys or observational data (e.g. (Choi, Lee and Yoo 2010); (Vlaar, van Fenema and Tiwari 2008); (Vaast and Walsham 2009)). Even research on the adoption of IT systems has made extensive use of non-electronic data sources (e.g. (Thomas and Bostrom 2010); (Du and Flynn 2010); (Laumer and Eckhardt 2010)). We have identified a number of exemplar topics in the IS literature that could benefit from Sociometric Badge data to provide starting points for researchers to begin using the Sociometric Badges. We performed an extensive survey of the recent IS literature, examining all articles from the last 5 years of MISQ and ISR, and the last 3 years of ICIS proceedings to identify exemplar topics in IS that can benefit from use of the Sociometric Badges. Below we describe how badges can contribute to each of these areas in the context of the research opportunities identified in the previous section.

Knowledge Sharing

There is a long stream of research that investigates the motivations (Hendriks 1999), mechanisms (Massey and Montoya-Weiss 2006) and influences on (Bock, et al. 2005) knowledge sharing. Social interactions have been identified as an important factor in how and

when knowledge is shared (Yu, et al. 2010). The additional data collected by the Sociometric Badge provides a number of opportunities for research in this area.

Thin Slices. The field of IS has studied the implications of team knowledge sharing (Choi, Lee and Yoo 2010), but the interactional dynamics of knowledge sharing events, such as team meetings, has not been thoroughly examined. The dynamics of interactions have important implications for how effectively knowledge is transferred and how well teams perform (Shaw 1976). It may be that one-on-one discussions are better for knowledge sharing than group discussions in some cases, while in other cases presentations might work better. The Sociometric Badge collects data that can be useful in understanding these dynamics, such as turn taking patterns and speaking speed, in real time using the microphones and radios to determine who is participating in group discussions. These types of interactional dynamics relate to participant engagement in discussions and by extension knowledge sharing (Curhan and Pentland 2007).

In the context of the larger organization, facilitating effective knowledge sharing between teams is challenging (Kotlarsky, van den Hooff and Huysman 2009). This difficulty is often viewed as purely related to the content of discussions, since different groups will use different terminology and have different tacit knowledge to draw from. An open question is whether differences in group behavioral norms, such as conversational style or when and where teams interact, have an impact on knowledge sharing. The Sociometric Badge can measure conversational style by combining turn-taking and speech features with posture data from the accelerometer. The radio combined with microphone and IR data can also determine where and when interactions are taking place. Sociometric Badge studies across different groups that

interact with each other could measure the effect of differences in behavioral norms on team knowledge sharing and effectiveness.

Fine-Grained Longitudinal Studies. IT systems are used to facilitate knowledge sharing, but it is often difficult to measure their effect beyond the activity recorded online. Vaast and Walsham (2009) for example performed a longitudinal study of a Web-based IT system that was meant to help people share knowledge. They identified geographic distance as a key factor governing how practices and relationships changed. Using Sociometric Badges, it is possible to extend this work with more fine-grained analysis by measuring the distance between desks in a single office. The badge's radio can automatically recognize desk location, and face-to-face interactions can be detected by combining IR, proximity, and microphone data. This line of research has already shown some promise. Liu (2010) showed the probability of people interacting over e-mail is inversely proportional to desk distance.

Social networking sites, blogs, and other communication tools have been viewed as a solution to knowledge sharing (Sims, Powell and Vidgen 2008). However it is still unclear how these systems impact information sharing in the physical world or whether they trade-off with face-to-face interaction. It may be that after reading someone's blog or speaking with them online, one's face-to-face conversational dynamics with that person change (turn-taking patterns, speaking speed). This would tell us what sorts of interactions and relationships these technologies are capable of fostering in the physical world.

Longitudinal micro-behavioral studies can also help us understand how people learn from knowledge transfers. Deng and Chandler (2010) identified knowledge networks and network position as key drivers of effective learning, but their cross sectional surveys were unable to capture changes in networks over time. The Sociometric Badge can use IR and microphone data

to detect dynamic changes and explore possible relationships with learning effects: when people become more knowledgeable do they change their networks to connect to people in different specializations, or do they become sought after interaction partners for those seeking expertise on their topics of expertise (engendering more connections with people in their own discipline)?

Changes in networks can also be linked to changes in emotional commitment in teams (Yu, et al. 2010). Emotional commitment could be measured by the badge using body language data, such as mimicry and energy, as well as speaking styles, such as speed and interactivity (Kim, et al. 2008); (Curhan and Pentland 2007). While Yu et al. (2010) measured emotional commitment at the team level, this commitment may be based in part on affective commitment in dyadic relationships. Teams with changing boundaries have also become common (Ancona, Bresman and Kaeufer 2002). Using Sociometric Badges, it would be possible to observe new team members and their effect on commitment and the network as a whole.

Theories that deal with changing teams and their knowledge output have also been developed recently within IS. Habib (2008) identified seven interdependent stages that determine a trajectory of knowledge creation. Key aspects of these stages include how members of a team interact with each other and the wider organization. Because of the difficulty of collecting data on interactions for a large number of teams, it was not possible to objectively link team behavior at each stage to success. Sociometric Badges however provide an opportunity to test this theory across many teams to observe whether real interaction dynamics, recognized using IR and microphone data, match the ideal at each stage and what implications this has for performance.

Informal Interaction Analysis. Levina and Vaast (2005) showed that people who span organizational boundaries facilitate cross-fertilization. Sociometric Badge data could enable us

to study the emergence of these boundary spanners, in particular if they are created through serendipitous interactions or through social status. Social status can be sensed by observing changes in body language mimicry, while serendipitous interactions can be recognized by combining location data from the radio with interaction data.

Information Worker Productivity

Information workers are heavily dependent on communication and researchers have analyzed their communication patterns using e-mail data and surveys (Aral and Van Alstyne 2010); (Aral, Brynjolfsson and Van Alstyne 2006). Face-to-face communication is still crucial for information workers, but it has been difficult to assess how the face-to-face relationships and social norms developed through physical interaction affect information work.

Thin Slices. Information workers face the challenge of trying to communicate with a wide variety of people from different cultures and backgrounds while at the same time respecting the social norms of these disparate groups (Rai, Maruping, and Venkatesh 2009); (Rutner, Hardgrave and McKnight 2008). Thin slices research is particularly relevant to this problem since slight changes in speaking speed or interruption behavior can strongly affect the trust formed with collaborators. As Rai et al. (2009) showed, this has direct implications for performance. Trust can be estimated with the Sociometric Badge using variations in pitch and volume (Waber, Williams, et al. To Appear), and some cultural differences in interaction norms can be captured using information on tone, speaking speed, and turn taking patterns in conversations. Sociometric Badge data will help validate subjective assessments of these quantities. Navigating a number of different relationships can take an emotional toll, and recent research has suggested that suppressing one's true emotions can have a negative impact on job satisfaction and exhaustion in IT professionals (Rutner, Hardgrave and McKnight 2008). This

emotional dissonance could be measured by observing an individual's actual emotional display using information on speaking speed and body language.

Informal Interaction Analysis. While connecting to disparate groups may be stressful, it can afford an information worker with a number of advantages through access to unique information (Aral and Van Alstyne 2010). The structure of a person's network and their organization's network as a whole have important effects on performance (Burt 1992), and constitute part of the culture of an organization. In IS there has been a growing focus on understanding the relationship between these networks and IT capability (Xiao and Dasgupta 2009) as well as combining online and offline interactions to understand how different networks contribute to performance (Zhang, Venkatesh and Huang 2008). The Sociometric Badge makes it easy to collect networked interaction data. Recent work also tries to distinguish different kinds of relationship networks (e.g. Friendship, advice, trust) (Madsen and Matook 2010). These relationships may be recognized using badges by analyzing information on the location (e.g. break room vs. meeting room) as well as the style of interaction.

Studies of Software Development

Software developers are frequently the subject of IS research, since they are not only information workers but also the creators of information systems. Researchers have used surveys and observational data to study the dynamics of different styles of software development, from pair programming (Balijepally, et al. 2009) to agile development (Vidgen and Wang 2009). What makes this area attractive for research with the Sociometric Badge is the plethora of electronic data available in the software development context and the importance of strong communication practices. The combination of these data sources can enable researchers to study phenomena that were not amenable to study before the introduction of sensing technology.

Thin Slices. Despite the emphasis on communication in software development, communication dynamics are rarely considered. Baljepally et al. (2009) compared pairs of collaborating programmers to individuals working alone and did not find any difference in their performance. Collaborative ability was not gauged in their study and it could be useful to examine the behaviors that successful pairs engaged in, such as equal participation, interactive turn taking, or the high performer speaking for a greater percentage of time. These attributes may explain more of the variation in agile software development performance than whether the programmers worked together or alone.

Fine-Grained Longitudinal Studies. Human observers have been used in longitudinal studies of interaction dynamics in software teams to get a better understanding of how the development process works (Vidgen and Wang 2009). Some research focuses on how the development of a shared language leads to increased IS development effectiveness (Charaf, Rosenkranz and Holten 2010). Beyond language, however, there are a number of social signals passed between people that indicate a level of shared cultural understanding (Pentland 2008). These signals might be speaking speed, turn taking, tone, and similarity in posture (Chartrand and Bargh 1999). By observing these quantities changing over time we might be able to develop causal models of how both language and cultural understanding impact software development success.

Informal Interaction Analysis. Social network effects have also been studied in software development. Fisk et al. (2010) investigated how boundary spanning roles influenced the success of IS development projects. While formal roles are important, informal boundary spanning should also be considered, since in many organizations informal interaction is a major source of boundary spanning (Burt 1992). Using IR and microphone data it is possible to learn

who in large organizations are speaking to each other and compare the effectiveness of this kind of boundary spanning with formal prescribed roles. It may be that encouraging informal boundary spanning is more effective than creating formal boundary spanning roles and this could be tested. Alternatively, it may be that the success of the formal roles creates more informal opportunities for interaction.

IS Adoption and Deployment

IS adoption is a process that mixes rational decision making within a formal and informal organizational structure. Using Sociometric Badges, it becomes possible to quantify certain aspects of the social context of IS adoption that have not yet been examined.

Thin Slices. One of the first steps in IS adoption is establishing a rapport between the IS developer and the client. Researchers have been studying the “best way” to facilitate meetings between the two (Majchrzak, et al. 2005). While Majchrzak and her colleagues primarily examined the content of early meetings, badges could estimate just how engaged the clients and developers were using speaking speed, average turn length, and speech volume. By combining data on conversational dynamics and information content, correlations with “learning” might be uncovered, providing hints as to how to best to facilitate early meetings.

Fine-Grained Longitudinal Studies. If new IT is rolled out improperly (e.g. too fast, not getting buy-in from the right people) it can spur rejection from key stakeholders (Laumer and Eckhardt 2010). Individual factors (i.e. personality) and social context have been identified as key elements of this process, but studies to date have not been able to determine if such factors change over time. Sociometric Badges could measure changes in anxiousness by measuring changes in the variance of movement patterns, and this could be mapped onto face-to-face interactions. For example, after an announcement about a new information system is made,

researchers could observe how an individual's anxiousness increases or decreases over time and whether this is influenced by the anxiousness of peers.

Interactions among peers has been identified as an important factor in IS adoption in qualitative studies (Silva and Hirschheim 2007). The Sociometric Badge can connect observations to behavioral data using data from meetings (sensed using proximity data). Badges can detect when employees become comfortable with the new system if pro-adopters speak persuasively during meetings. Persuasiveness is inferred using volume and speaking speed information. It would also be interesting to examine changes in the volume of interactions or engagement in conversations over time. This approach complements previous work examining the content of interactions rather than their dynamics (Iivari and Huisman 2007). Combining these data could give us a measure of the relative importance of interaction and engagement.

Geographically dispersed teams also have IS adoption challenges. This represents an interesting research opportunity. Thomas and Bostrom (2010) identified trust and relationship inadequacy as potential roadblocks to information communication technology (ICT) adaptation. Badge data could be used to gauge the level of trust between people using changes in speaking emphasis patterns. By combining these badge features with information from IT systems, researchers could compare how members who are occasionally co-located communicate using IT and face-to-face interaction. These results could then be used to gauge trust among distributed members.

Informal Interaction Analysis. When deploying new information systems, it is important to consider how they fit with the IT governance structure (Tiwana 2009). But informal social structure will also have an effect on IS deployment. If a socially powerful person is in a client department, then they may be able to exercise a degree of control over the IT system even though

they might not have formal decision rights over it. By collecting information on who talks to whom in the organization, this informal structure could be combined with data on the formal reporting structure to tease apart the important factors in IS deployment.

Once a system is deployed, success depends in part on training. The technical complexity and interdependence of training tasks have been identified as important factors in this success (Sharma and Yetton 2007). The social effects of training have not been considered. Using badges, researchers could examine if access to experts influences training outcomes. It may also be that training socially important individuals is more likely to lead to success since the knowledge they gain in training may be more likely to spread to others in the organization (Barahona and Pentland 2006).

IT Use

Once IT is deployed, use of the systems is usually studied by combining qualitative observations with survey data or data from the system itself (Iacovou, Thompson and Smith 2009) ; (Sherif, Zmud and Browne 2006). Previous studies have observed the effects of formal and informal roles (Davis and Hufnagel 2007), emotions (Beaudry and Pinsonneault 2010) and social structure (Davidson and Chismar 2007) on IS use. Sociometric Badges offer an opportunity to see these effects at a micro-scale as well as over longer periods of time. Connecting badge data to electronic data sources from information systems themselves also opens new opportunities for IS researchers.

Thin Slices. Communication between different management levels is critical to promoting effective IS use (Iacovou, Thompson and Smith 2009). The challenge is that there are often conflicting pressures between accurate reporting and a desire for the appearance of progress. Iacovou et al. (2009) showed power, trust, and the quality of communication between

project managers and executives were directly linked to selective reporting. While they took a survey-based approach to understanding this problem, Sociometric Badges can assess these quantities using observed behavioral data. Power can be assessed by looking at how interaction with the executive changes the turn taking practices and speaking speed of managers (Choudhury and Pentland 2003). Trust can be assessed using emphasis (Waber, Williams, et al. To Appear) and communication quality can be examined by looking at the balance of participation and speaking speed (Kim, et al. 2008). Such analyses could validate prior results on IS use with precise behavioral data and enable analysis of changes in power and trust dynamics over time.

In some cases, however, conflicts arise with the introduction of disruptive IT innovations (Sherif, Zmud and Browne 2006). Sociometric Badges could be instrumental in detecting conflict episodes by using speaking speed and interruption information, as an abnormal number of interruptions can predict discord (Kollock, Blumstein and Schwartz 1985). This could also allow for just in time managerial interventions that would automatically respond to contentious social conditions and enable managers to step in and diffuse growing discontent with a new IT system.

Fine-Grained Longitudinal Studies. Organizations change their usage of IT systems over time and Sociometric Badges are uniquely positioned to observe fine-grained changes in the social context in which IT use changes. Workers normally become used to new information systems over time, as seen through changes in emotional displays (Beaudry and Pinsonneault 2010) and stress levels (Ragu-Nathan, et al. 2008). Sociometric Badge data allows emotion tracking over time to gauge how effectively new IT systems are integrated into the organization.

Specifically, excitement, happiness, anger, and stress can all be sensed using the Sociometric Badge. Excitement is measured using volume modulation and speaking speed,

while happiness is correlated with variance in movement (Yano, et al. 2009). Anger can be measured during interactions as the amount of interruptions and speaking over another person (Kim, et al. 2008). Finally, as we found above in our call center study, stress can be measured by looking at changes in the constraint of an individual's face-to-face network as well as variance in movement.

These individual effects may be in response to the changes in a person's role due to the introduction of a new IS (Davis and Hufnagel 2007); (Banker, Bardhan and Asdemir 2006). Davis and Hufnagel (2007) showed that new information systems can change an individual's status as an expert and that the structure of teams can also be greatly affected by new IS deployment. Sociometric Badges can measure status changes using speaking influence data as well as changes in posture during interactions, while team structure can be measured through interaction data. By studying these changes over longer periods of time, researchers can observe whether team structure and expertise return to their original state after an initial adaptation period or whether these features take off on entirely new trajectories. Combining software usage information with badge data could also help researchers identify what parts of the new IS were causing changes in communication and behavioral patterns.

Mergers and acquisitions also cause large changes in both the IT systems and social systems of the combining organizations (Niederman and Baker 2009). Using the Sociometric Badges, it would be possible to see how socially integrated the merged firms become using data on interactions. By adding data on IS integration, researchers could investigate how changes in communication patterns relate to changes in the integration status of IS components.

Informal Interaction Analysis. Information systems often result in new social links between previously isolated departments (Davidson and Chismar 2007). This may be due to

changes in the governance structure of the IT system and the match between these structures has been shown to increase IS effectiveness (Tiwana and Konsynski 2010). Sociometric Badges could extend this analysis to informal communication links between departments using interaction data. An individual's network position is a significant predictor of IS use (Sykes, Venkatesh and Gosain 2009). Badges can not only detect the network, but also help determine if IS use is a precursor to network centrality through increased expertise or alternatively if a central network position puts pressure on an individual to use information systems.

Media Choice

Media choice is an obvious area of application for the Sociometric Badge. Using surveys and human observation it is hard to obtain an accurate view of face-to-face communication, while it is comparatively easier to mine logs of electronic communication. By combining these different data streams it will be possible to more accurately answer questions related to media choice as well as to compare use of different media at micro timescales.

Thin Slices. While the effectiveness of different communication channels is often discussed as independent of social context, Robert et al. (2008) showed that a team's pre-existing social capital affects their ability to collaborate using lean digital media. They used surveys to gauge a team's social capital before their experiment, which the badges could measure using interaction data, but in their study they artificially isolated teams or situated them in the same room to exact an amount of observational control on the interactions. Instead, badges could be used to observe naturally occurring situations to see if face-to-face dynamics are replicated when the same team communicates using different media.

Fine-Grained Longitudinal Studies. While social capital relates to how effectively groups can utilize different communication media, changes in the levels of trust and

understanding in a group change what communication media groups use (Massey and Montoya-Weiss 2006). Sociometric Badges can track these changes using data on emphasis to see how trust changes over time. Combining these observations with face-to-face interaction data and electronic communication data, researchers could analyze how micro-level changes in trust relate to media choices at different points in time.

New events and tasks change the media groups use to communicate (Dennis, Fuller and Valacich 2008). Constantinides et al. (2008) studied how emergency responders coordinated in a geographically distributed setting using IT. Combining data from IT systems with face-to-face interaction data from the badges could show how different events caused different uses of communication media (broad impact events vs. locally important events, emergencies vs. non-emergencies). This approach would also allow researchers to study different stages of an event, since rich media such as face-to-face may be used at the onset of an event to assess the situation, while ICT may be used to broadcast information to less relevant stakeholders.

New ICT can also be introduced into organizations, and in addition to creating new usage structures and routines it may affect how other communication channels are used (Watson-Manheim and Belanger 2007). Sociometric Badges could be deployed in organizations undergoing such changes to determine if the introduction of new technologies curtails certain types of face-to-face interactions or encourages new ones to develop. Ng et al. (2010) examined how power affects how hospital employees communicate using a new web-based messaging system. Observation of changes in face-to-face interactions could be added to the electronic communication that was observed in this study to understand how status signifiers such as interruptions and turn taking patterns changed after the introduction of new technology.

Informal Interaction Analysis. While an organization may have a number of ICT systems at its disposal that does not mean that all channels are simultaneously available. Face-to-face communication in particular may not be feasible if people are located in different buildings or too far away in the same office. Similarly, some systems may not be available if a person is away from their computer. Snyder and Lee-Partridge (2009) used surveys to examine how people choose different communication channels depending on their availability. Badges could more accurately assess availability by using location information to determine whether or not employees were near computers or each other. Badges can also recognize if someone is already in conversation, signaling their unavailability. Combining these data with knowledge of the types of information someone was seeking could give a robust view on how individuals make different media choices in different contexts.

In Table 19 we summarize some of the potential contributions of the Sociometric Badge to each of these research areas.

Topic	Body Language	Networks	Conversational Dynamics	Location Traces
Knowledge Sharing		Network change, network position, and relationship to sharing	Effectiveness of team meeting knowledge transfer	Effect of different meeting places, distance between people
Info. Worker Productivity	Emotional dissonance in conversations	Network relationship to productivity, types of networks	Trust and culture differences and productivity impact	Types of relationships between workers
Software Development	Collaborative ability of software teams, cultural understanding	Boundary spanning and relationship to formal roles	Cultural understanding	
IS Adoption and Deployment	Anxiousness changes as a result of IS adoption	Network position, social power relationship to changes in IS acceptance, social effects of training	Conversational rapport and relationship to learning in meetings, persuasiveness and social power of pro-adopters	Recognize meetings, co-location
IS Use	Assess emotions, social power of employees and relationship to IS use	Changing roles, social integration and match with IT governance, network precursors of IS use	Social power, trust, communication quality and relationship to IS use reporting, detection of conflict	
Media Choice		Social capital	Relationship to ICT	Communication

assessment, face-to-face interactions, relationship to events	communication dynamics, changes in trust, communication channel availability	channel availability
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Table 19. Potential Contributions of the Sociometric Badge to Key IS Research Topics.

Research Design: Key Trade-offs and Design Choices

The Sociometric Badge enables a departure from previous constraints on data granularity, study breadth, and exploratory research. These features of the badge data collection process provide new opportunities for research in specific research areas in the management literature. At the same time however, a number of trade-offs in research design have to be considered. These trade-offs are manifest at all levels of a research study: how data is collected, what data is collected, and how data is analyzed. We discuss each of these tradeoffs and their implications for research that uses Sociometric Badges for observation and data collection.

Privacy vs. Granularity

Privacy is one of the main concerns of any social science study participant. For some participants the Sociometric Badge conjures Orwellian visions of their managers tracking them through the workplace or listening to their every word. The Sociometric Badges are technically capable of recording such information, so it is up to the researcher to determine what data is appropriate to collect, how data collection choices impact participant privacy, how not put participants at undue risk, and how to achieve truly informed consent.

Unlike electronic communication data, researchers have greater control over the granularity of the data they collect with Sociometric Badges which has direct privacy implications. If audio samples are recorded at a fast enough rate, words can be reconstructed. If radio transmissions are made frequently enough, the precise path a person takes through an office can be tracked. Depending on where base stations are deployed, private areas of the workplace (e.g. washrooms) can potentially be included in data collection.

Some research questions require access to data at these levels of granularity. For example, raw audio is useful in studies that examine word usage or spoken language in cross-cultural settings. A higher level of granularity may also be useful for studies of the impact of office layout and design on the movement of workers through space on their informal face-to-face interaction. Researchers must therefore balance the benefits of these granular data collection opportunities with privacy concerns and requirements of informed consent. Study protocols can explicitly bound raw audio and movement data collection by restricting the frequency of data sampling algorithms and limiting sensing to specific locations like meeting rooms or controlled laboratory studies.

Location tracking might on the surface seem more benign, since with fixed-point base stations it is only possible to track a participant's location within the workplace. However, there is a strong qualitative difference between knowing what room someone is in by sending a radio broadcast once a minute and knowing when a person takes a single step by broadcasting once a second. Depending on the organization's culture, this might be considered an unacceptable invasion of privacy. Researchers may be able to sidestep this problem by negotiating with stakeholders to ensure that this data is only collected in "public" places such as hallways between work areas or by only collecting fine-grained location data from a subset of enthusiastic and willing study participants.

Thus, a key tradeoff researchers must consider when designing a badge study is the increasing invasiveness of more granular data collection (location sensing, raw audio collection and the frequency of sampling rates) and the increasing precision of the data collected. In some instances it will be useful to spend the extra effort required to convince a smaller number of study subjects to consent to more granular study in a controlled environment, for example if the

researcher wants to assess detailed movement data or language use. However, in most cases, a lower level of granularity (which still far exceeds that achieved with surveys or even electronic communication data) is sufficient for assessment of the phenomenon under investigation. Choosing the right level of granularity is a matter of balancing privacy considerations with the benefits of finer grained data.

Exploratory vs. Confirmatory Research

A common challenge in social science research is managing the tension between exploration of new intellectual territory and testing of existing theories. When new data collection methods emerge, relatively unknown areas are opened which are often difficult to interpret or reconcile with existing empirical findings, making it difficult to navigate this tension. The Sociometric Badges are capable of examining phenomena that were not conceivable in the past, so researchers have to determine an appropriate balance between exploratory and confirmatory research.

To date Sociometric Badges have not been employed widely in management research, which could lead researchers towards relying on theories developed using survey and electronic communication data. Research in this vein would use the badge as a direct substitute for these other data collection methodologies. Initially this would fit in nicely with the informal interaction analysis research opportunities that we identified above.

Opportunities such as thin slices and fine-grained longitudinal studies, however, may require more exploratory work as the Sociometric Badges start to be adopted by the management community. It was simply not possible to observe conversational dynamics in a series of meetings or how emotions change over time in relation to IT system changes. These opportunities have few corollaries in current management theory, and new theories will have to

be developed for progress to be made. This will require exploratory research to sift through initial possibilities and connect this unique data with prior work in management.

The key design choice for researchers is to balance their research goals with the Sociometric Badge with the type of research that is most needed by the management community at large. This is not to say that researchers need to ignore their predisposition towards exploratory or confirmatory research, and different research questions require different approaches. The Sociometric Badges, however, present a unique challenge in that for some areas exploratory research is essential for it to reach its full potential. Adding exploratory elements to confirmatory studies and theory building to exploratory studies will be important in the initial stages of research to manage this tension and move the management literature forward.

Observation vs. Feedback

One of the modern tenets of social science is that the researcher should not be involved in the study, although it's never possible for this ideal to be achieved. It is viewed as desirable if the observer can blend into the background, and that any data collection not affect the behavior of subjects. With electronic data collection this is often not an issue, since monitoring is not readily apparent to participants. In studies with human observers, as with Sociometric Badges, however, there is undoubtedly an effect on behavior. As the classic Hawthorne effect demonstrates, sometimes by just observing a phenomenon one can change it. These effects will diminish over time, however, as subjects are acclimatized to the observation (Versloot, et al. 1992).

In our experience with the Sociometric Badge, we have observed similar behavior. For the first few days subjects are intrigued by the technology and will try harder to face others when in conversation so that data on their interaction will be captured, but after this initial phase,

wearing the badge typically becomes routine. We have even observed participants forget that they are wearing the badge and accidentally take it home with them.

This highlights one challenge that we frequently encounter in research with the badge. Without feedback, people have less of a sense of the value of the study to them. While it is not a large burden to put on a badge every day, it does take a small amount of time and can occasionally be uncomfortable. There is also sometimes mild social pressure on participants if they are part of a larger population where not everyone wears badges, making them stand out. These inconveniences can weigh on participants, and after a month or two it may make them more likely to drop out of the study.

The issue for researchers is that providing feedback helps engage study participants in the research, gives them value and keeps them interested in participating, but at the same time inserts the researcher directly into the social environment they are studying. This is especially true in studies designed to explicitly test the value of real time feedback in changing behaviors. Technically, feedback is simple to provide, and in some of our studies we have used simple features to provide study participants with a sense of whether their behavior is typical or not. For example, we have shown what percentile someone is in for their “movement level,” which uses accelerometer data to measure the energy in their motion. With appropriate research design the feedback can become a part of the study. As we discussed above, there is an opportunity with real-time feedback to change not only research, but the way that organizations are managed. Experimenting with different feedback mechanisms (e.g. e-mail notifications, dashboards, and social comparison feedback) may become a major part of research with the Sociometric Badge in the future, and represents an interesting new area of exploration.

The key design choice is in either minimizing researcher involvement or in directly intervening in the research context by providing feedback. In the first instance, the goal is to collect behavior data as it would be seen without observation. In the second instance, the goal is to directly test the effects of interventions. Considering the costs and benefits of each and designing badge studies with each of these effects in mind is essential.

Challenges to the use of Sociometric Badges in Research

The opportunities enabled by the Sociometric Badges could contribute new insights to IS and management research, but they also present some challenges for researchers. Since this methodology is quite different from the way studies have been conducted in the past, it will require us to approach problems differently.

First, the focus of analysis shifts from self-reported perceptions to behavioral observations that may not be the phenomenon researchers are interested in measuring. For example, researchers interested in power may ask questions on that topic directly in surveys, but they would have to determine what behaviors exhibited by participants have a bearing on power. This is a formidable challenge, as the research on behavioral indicators of outcomes in the social sciences almost exclusively relies on human coders in laboratory settings. Pilot studies and exploratory research may help overcome this obstacle by verifying initial hypotheses on a small scale in real world settings and showing the promise of previously unexamined behaviors.

Second, behaviors can have very different meanings in different contexts, which can make interpreting data from the Sociometric Badge challenging. In the context of a lunch time discussion of a television show, for example, shouting may imply interest and engagement, while the same behavior at a meeting might signal discord. It will become important for researchers to choose research questions that should generalize well across different contexts or find ways of

recognizing context. Using location data from the badges or data from appointment calendars may provide adequate information on context, but interviews and other qualitative data may be necessary to help tease apart the different contexts in a study.

Third, the management community will need to insist that researchers make their data processing algorithms available to the community at large. In order for researchers to adequately compare results across different studies, they have to be sure that they are comparing the same features. This problem exists at a smaller scale with survey research, since different survey instruments can be used to answer the same question. With the Sociometric Badges, however, this problem can be overcome more easily. If data has been collected at a similar level of granularity then researchers can use one data processing algorithm to extract the same behavioral features from different datasets. This free flow of algorithms would allow the management community to more easily determine the appropriate metrics for measuring different phenomenon as well as provide researchers with a powerful platform to build on top of previous research.

7.3. Network Constraint Terminology

The term constraint has a number of negative connotations, in contrast to other network measures such as betweenness and degree. This misconception mainly stems from Burt's perspective (Burt 1992), where constraint is viewed across all of our networks rather than confined to a single organization. A "constrained" network in this sense would imply a lack of diversity of information about new opportunities and ideas, and has been linked to difficulty finding jobs (Granovetter 1973).

When examining networks within organizations, however, this same concept takes on new meaning. Networks high in "constraint" would not be very constraining since people are

privy to similar sources of information. Instead, in the organizational context a network high in constraint would be more effective at information clearing (checking information and having in-depth discussions with peers). In the above studies we have consistently showed that, rather than constraining the actions of individuals, embedded individuals are more effective and have better overall outcomes than those with networks rich in structural holes.

To remove misconceptions around these densely connected networks and reduce the use of biased terminology, we advocate renaming network constraint “kith.” “Kith and kin” is a thousand year-old phrase that is still familiar although “kith” alone has fallen out of use. The word “kith” comes from the old English and old German words for “knowledge,” and it means “a more or less cohesive group with common beliefs and customs.” These are also the roots for “couth,” which means to act with a high degree of sophistication. Your kith is the circle of peers that you compare yourself to, copy, and use to validate ideas, and thus they are the people from whom you learn adaptive habits of action (Pentland 2010).

This new conceptualization of network constraint as kith may require a new formula to more thoroughly distinguish the two. Ideally this formula would strike a balance between having a large group and having a densely connected group. We hope that the discussion and results presented here will spark debate in the social network community around terminology and spur additional research in the area of kith/constraint.

Chapter 8

Conclusion

While there has been strengthening of forces pushing organizations to rely more heavily on remote collaboration (Jarvenpaa and Leidner 1999), in this thesis we have demonstrated the importance of social support and face-to-face interactions. We showed that social support, operationalized as network constraint, was in the aggregate positively related to job satisfaction, productivity, and lower stress. We also showed that changes in social support were strongly related to changes in job satisfaction. Finally, we were able to increase social support by manipulating break structure in a call center. This change also led to higher productivity, although we were not able to show this at the individual level. Finally, through qualitative observations we discovered that large and small group interactions were major contributors to social support and that company events had significant impacts on behavior and outcomes.

Many of these behaviors will be difficult to replicate in distributed settings with a purely technological solution. As we saw in our participant observation work, serendipitous interactions and co-located events are major drivers of important outcomes. One of the challenges for industry moving forward is how to cope with these competing challenges. An interesting point to come out of the Travelco study was that large group interactions were the biggest contributor to social support. This indicates the importance of having larger co-located events before and during distributed projects. However, if only members on the team itself are included, the broad perspective that is gained from larger group interactions is lost, so it may be advantageous to invite additional employees from each location to attend.

As our results have shown, there is great potential for the Sociometric Badges to open new opportunities for both exploratory and confirmatory research in management scholarship. Badges can detect face-to-face interactions over time, record the activity and movement of study participants through office spaces, help assess conversational dynamics amongst pairs of individuals or larger groups, and collect data on physical location and proximity. These capabilities enable observation of fine-grained behaviors and interactions at low cost, making feasible the study of "thin-slice" behavioral dynamics, longitudinal observation of micro-level behaviors, and informal interaction over time. Using these new data collection techniques, researchers can address previously intractable research questions, both in existing lines of research fundamental to management scholarship and in new lines of research that we are yet to explore.

These new data could also support new management methods. Beyond obtaining better data on management strategies and their effects on behavior, we can imagine new ways of managing people, making full use of the real-time nature of these data. We have already experimented with giving real-time feedback in meetings, but these efforts can be extended to the manipulation of physical office environments, employee training, and recommendations concerning organizational structure and team assignment.

As is typical with new research methodologies, new opportunities are accompanied by new challenges and research design decisions. We have highlighted several important limitations to research using the Sociometric Badge as well as some key trade-offs in research design such as the need to balance the level of granularity in data capture with participant privacy. We believe the use of Sociometric Badges in research could portend a dramatic

improvement in our understanding of human behavior at unprecedented levels of granularity and we hope that other researchers will join us in this exciting new area.

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