SKILL IN INTERPERSONAL NETWORKS

by

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Chapter I: Introduction

How do people navigate social structures within their work environment, to achieve their work objectives and advance their careers? Social network research has shown that interpersonal relationships are important drivers of career success: Relationships that a person builds within and beyond the organization provide important access to novel and valuable information (Burt 1992; Granovetter 1973), legitimacy within the organization (Burt 1998), mentoring and other identity-based flows (Podolny and Baron 1997), and social support (Ibarra 1995). In short, relationships have substantial impact on individuals' performance and career mobility through job offers and promotions. Yet, although we know that individuals' networks vary in composition and structure, for instance, across race and gender (Burt 1998; Ibarra 1995), we have little understanding of the day-to-day interactional strategies and practices that people actually employ to successfully use their networks. Moreover, we also have little understanding of the cognitive antecedents of network advantage – what cognitive processes provide the ability to learn those day-to-day interactional strategies?

In this dissertation, I study the cognitive and behavioral skills that people use to navigate social networks at work, via three separate but related papers. These papers explore in different ways how people obtain advantages – such as higher information flows or greater ability to accurately perceive their social environment – through interactions with others. Paper 1 argues that relational schemas, which are the cognitive schemas that people use to guide interactions with other people (Baldwin 1992), are developed over time through exposure to others. However, a tension exists: Having a lower variety of schemas (employing generic schemas which are used in multiple relationships) enables a person to interact with more people using fewer cognitive resources (Abelson 1981), but having a greater variety of schemas (when one has unique schemas for each relation) enables a person to better adapt to the needs of each relationship. Using in-depth interviews, network data, and interaction data from an administrative department of a manufacturing organization, I find a curvilinear relationship between both social experience and network contacts in an environment and the degree to which people develop more specific relational schemas, providing evidence for this tension between the need to adapt to each relationship versus the constraint of cognitive overload. These findings highlight the ways in which social processes affect relational cognition within organizations.

In Paper 2, I argue that social network position cannot precisely measure access to information flows in a social context. I develop a new method for measuring access to information, using time-ordered communication/interaction data, which accounts for the temporal ordering of communication and the constraints of time, scheduling, and other factors that cause variation in the frequency of communication across and within relationships.

In Paper 3, I then focus on relational acumen, which is the ability to accurately perceive the strength of one's relationships. Relational acumen is a form of network perception accuracy, a cognitive skill that provides a basis of power in organizations (Krackhardt 1990). I argue that people who have higher access to social information flows have greater relational acumen. Again using data from the same organization, I find that people who occupy positions of network brokerage have greater relational acumen – they are more accurate in perceiving their strong ties. More importantly, I find that having interactions that are in the midst of others' interactions throughout the day (what I call "interaction efficiency") provides the greatest benefit for relational acumen. Thus, how one interacts with contacts matters more than who one's contacts are.

Chapter II: Site and Data

Site

All three of the papers in this dissertation utilize data from a single organization. Multi-method longitudinal data was collected from an administrative department of ManuCorp[1], a large manufacturing company in the U.S. Midwest. At the beginning of the data collection, the department employed 37 full-time employees who were located onsite. During the two year period of data collection, 5 people left the department (due to retirements, job changes within the company, turnover, and employee illness), and 2 people were brought into the department. Individuals who were formally part of the department but worked offsite were not included in this analysis[2]. The majority of employees are engineers or scientists by training, ranging from chemical engineers and chemists, to mechanical engineers, to biologists and geologists. About 60% have advanced university degrees. Also, about 60% are male, and only two (5%) are visible racial minorities. This department is made up of several internal groups, and including the director of the department (who is the highest level), it has three levels of managers. As is typical of much white collar work, all employees must work extensively with many of their colleagues within as well as outside of the department to accomplish their jobs. While the group included a

[1] Pseudonyms are used for the company and all its employees. Conducting social network research requires that data collected not be anonymous (identifying information is retained in the data). This is necessary to construct social networks and match different sources of data. However, all data was collected completely confidentially. ManuCorp management was not given individual-level data and was not aware of who agreed to participate. Individual consent was obtained for each stage of the research.

[2] In addition, three people employed by the department worked part-time onsite and part-time offsite (in other buildings), one person was not employed by the department but was present part-time, and an intern was hired for several months only at the end of the study. Those individuals were also excluded from this analysis.

couple newer hires, most employees had spent over a decade working for the company, with average tenure in the organization of 17 years; some as much as 30 years.

Data

Data collected include social networks, interaction data, personality data, and non-participant observations, collected in three phases. This type of data collection necessarily involves a tradeoff: In order to collect such rich data, particularly the interaction data, having a relatively small study site is necessary. This allowed the installation of equipment necessary for the movement tracking data collection, which would have been considerably more costly with a larger department or over multiple departments. In addition, having a small site made it possible for me to conduct extensive interviews about each participant's relationships with all of his or her colleagues in the department. Data at Time 1 and Time 2 was collected primarily by Felichism Kabo, with funding from a National Science Foundation grant (award number 0724675, principal investigator Jean Wiseman). I assisted with the data collection at Time 2. I collected all data at Time 3 with the support of a Ross School of Business Doctoral Studies Small Research Grant.

Time 1: Network Survey & Demographic Data Collection

At Time 1, an online survey was administered to collect social networks and demographic data. In the survey, respondents were presented with a full list of all employees in the department, and asked to identify individuals whom they did not know ("whom you interact with as a mere 'hello' or less"). The survey system then limited further questions to ask only about individuals they *did* know. Respondents were asked to rate the strength of their relationships with each other person "How strong a work relationship do you have with this person?" on a scale of 1 to 5. 1 = I prefer to avoid this person, 2 = Weak, 3 =

Somewhat weak, 4 = Somewhat Strong, 5 = Strong. In addition, respondents were asked to identify which individuals they either a) sought advice from or b) gave advice to. Demographic questions included educational background and time employed at ManuCorp. (Other demographic information such as sex and race were not included in the survey, but were identifiable via site visits.) Thirty-three out of thirty-seven full time onsite employees responded to the survey. In addition, the department provided an organization chart, identifying managers.

Using the survey responses, two separate social networks were constructed: The contact network consists of all relations where both individuals indicated knowing each other. The advice network consists of all relations where both individuals agreed that advice was given and/or sought. The advice network is a bi-directional network, which means that both partners agreed specifically on who was giving and/or receiving advice in each relationship.

Time 2: Movement Tracking via RFID System

At Time 2, one year after Time 1, a motion tracking system was installed in the department. Thirty-four people in the department (out of thirty-five fulltime onsite employees) participated in the motion tracking study[3], by wearing lanyards containing an RFID tracking device. Sensors installed throughout the ceiling of the department detected their movement for a period of nine weeks, recording each person's location in x, y, z space to the millisecond level. In total, over thirty-five million rows of data were collected indicating participants' movements. The recording area covered a single floor (see Figure 1, showing the floor plan of the office), which comprised all of the department's offices. On

[3] The missing person did consent to participate in the study, but technical problems caused his data to be unrecorded.

this floor, there is one actively used kitchen, one set of restrooms, and one elevator bank (for entry/exit), which increases the interaction between people from different parts of the floor. Using this data, interactions between people are assumed to occur when those people are within five feet of each other for more than thirty seconds. Over the course of the period studied, approximately 23,000 dyadic interactions occurred. With the exception of one dyad, everyone interacted with each other at least once during the period.

FIGURE 1: FLOOR PLAN OF MANUCORP DEPARTMENT

Time 3: Interviews, Personality Survey, and Observation

In the third phase, starting seven months after Time 2, I conducted in-person semi-structured interviews with employees in the department, over a period of two months. Thirty-three employees participated (out of thirty-four then present fulltime onsite employees), and twenty-four of them agreed to have their interviews recorded. Given the time constraints of participants, some interviews were as short as 30 minutes, while others extended beyond 2 hours. The average interview length was approximately 1.25 hours. In the interview, I presented participants with a sheet listing all of the department's employees and their prior answer (at Time 1) to the question "How strong a work relationship do you have with this person?" (If they had indicated that they did not know the person at Time 1, that person was listed with 0.) Interviewees were then asked to update their answers to how they felt currently about each person, writing corrections directly on the sheet. This data also provides an updated contact network at Time 3 (n=33).

I then asked each participant to describe the details of his or her histories and interactions with each colleague. I asked, "Tell me the story of how you got to know each person, and how that relationship evolved over time." I also asked "Describe a typical interaction with that person" in each case. Recorded interviews were transcribed, yielding rich narratives from each participant describing his or her relationships with others in the department (n=24).

At the end of each interview, interviewees were given a brief paper-based survey assessment of the Big Five personality traits, called the Ten Item Personality Inventory (TIPI) (Gosling, Rentfrow, and Swann Jr. 2003) (See Appendix 1). All but one interviewee returned a completed personality assessment after the interview (n=32). Ideally, a longer and more detailed survey instrument is used to measure personality. However in this setting, participants would have been resistant to completing a longer survey, resulting in a much lower response rate. In situations like this, the TIPI provides a compromise that yields reasonable measures of extraversion, openness, emotional stability, agreeableness and conscientiousness, while minimizing the time required to administer it (Gosling, Rentfrow, and Swann Jr. 2003).

Concurrent with interviewing, I conducted non-participant observation at the department for two months. I was present in the department for approximately 30 hours per week, observing the daily work activities and interactions of employees. I casually talked to everyone about their jobs and the department/company and listened to their work and social conversations. My interactions with everyone provided helpful background on individuals' work and interaction habits; thus, I could more quickly understand interviewees' stories of relating to each person. Finally, I'll note that while I did very minimal work for the department (I provided brief database consulting), I frequently brought homemade desserts into the office, which quickly introduced me to everyone and sparked many informal conversations. These experiences all helped in interpreting participants' interview data and provided a greater understanding of the department's context.

Chapter III: Relational Schemas and Cognitive Lumping (Paper 1)

SUMMARY

I explore the cognitive schemas and scripts that people use to guide interactions with other people (relational schemas (Baldwin 1992)). Using in-depth interviews of 24 of ManuCorp employees, I identify the relational schemas they employ for interacting with each of their other colleagues. I argue that the degree to which a person's relational schemas are more general or more specific to individual relations indicates how much the person cognitively "lumps" his or her relations – in other words, treats the relationships as being the same, rather than as unique and varied relations. Lumping is consistent with the "cognitive miser" perspective (Fiske and Taylor 1984), allowing people to simplify the mental models required for social interaction. However, a tension exists. Having a lower variety of schemas (in other words, having more general schemas which "lump" relations together) enables a person to interact with a wider range of people using fewer cognitive resources (Abelson 1981). But having a greater variety of schemas enables a person to better adapt to the needs of each relationship. I hypothesize that as people gain social experience in an environment, the degree to which they cognitively lump their relations decreases – because social experience promotes a higher cognitive capacity to deal with the complexity of having specific schemas for specific relations. However, this is true only to a certain point: at high levels of social experience, cognitive lumping should increase, in order to prevent cognitive overload. The findings of this study support the hypotheses, in particular that there are

curvilinear effects of a person's tenure in an organization and embeddedness in networks on his or her degree of cognitive lumping, and that cognitive lumping decreases a person's ability to accurately understand his or her relationships. This research highlights the ways in which social processes affect relational cognition in organizational contexts.

Introduction

Relational schemas are mental knowledge structures containing information about our relationships (Baldwin 1992). We use these schemas to guide our interaction with others: relational schemas tell us what to do when interacting with others in specific situations (Abelson 1981), and they help us choose among possible courses of action within relationships (Safran 1990). This study investigates the fundamental questions: How do we gain these schemas? And what are the tradeoffs in acquiring them? I argue that the development of relational schemas is driven by social experience and social embeddedness (Granovetter 1985); as people interact with others and acquire knowledge of others' relationships, they expand and refine their knowledge of how to interact with others. It may seem strange to suggest that there is a tradeoff in this process or a negative repercussion of acquiring more relational schemas. However, our ability to develop extensive schemas is limited by the cognitive overload that can be produced. Developing a greater variety of relational schemas is positive, in the sense of allowing individuals to better match their behaviors to their relational partners' expectations; in the extreme, having a specific and well-developed schema for interacting with each person allows one to better adapt to the needs of each relationship. On the other hand, reducing the variety of relational schemas one has – applying schemas generally, to interactions with multiple people – economizes on cognitive resources.

I begin by introducing the relational schema concept and how relational schemas structure our sensemaking of interpersonal interaction. Focusing on the organizational context, I derive hypotheses about how schemas develop greater variation (become more specific) as a result of social experience at work, but only up to a point. At higher levels of social experience at work, schemas become more generically applied to relational partners again. In order to better understand this tradeoff, I also hypothesize that as the variety of relational schemas increases, a person's ability to better understand his or her relations increases. These hypotheses are then tested using interviews, network data, and interaction data collected in an administrative department of ManuCorp. The goal for this study is to show how a person's social experience produces a greater cognitive capacity to understand and navigate the social environment.

RELATIONAL SCHEMAS

Schemas are mental models – knowledge structures that exist in our minds that help us selectively *attend* to information, *process* information, and *retain* information (Smith 1998). A simplified way of understanding schemas is just that they are "groupings" of information – bits of data and ideas that are associated together in a structured way. We employ schemas, like mental blueprints, to achieve all that we do, from riding the bus, to getting dressed, to writing an article. Schemas are how our brains store information, and they guide how we absorb what goes on around us and respond to it.

Cognitive researchers have found that the mental schemas we have for relationships and interaction are complex. A "relational schema" is a schema that is composed of an understanding of the self, an understanding of the other person, and a set of scripts that are invoked for interacting with that person (Abelson 1981; Baldwin 1992). Put generally, this represents “how I am when I’m with you”, “how you are when you’re with me”, and “what we do together”. More specifically, the understanding of the self is a self-schema, a “declarative knowledge structure consisting of specific facts, memories, generic descriptors, and so on” (Baldwin and Dandeneau 2005), and the understanding of the other is an other-schema, which is also a declarative knowledge structure that contains all that one knows of the other person. Scripts are a set of expectations for behavior, thoughts, goals, and feelings (Abelson 1981; Baldwin and Dandeneau 2005), sometimes described as “if-then” sequences, such as “if the person is behind me, then I will hold the door open” or “if my mother extends her cheek, then I will kiss it”. These provide the blueprint for creating interaction; knowing what to do next in an interaction is schema-driven. Relatedly, the ability to recognize “what we are doing,” or comprehend the meaning of a series of actions is also schema-driven.

To illustrate what a relational schema can look like, here is a small example. A student’s schema for a relationship with a professor might look like the following:

Self-Schema: “As a student I should be deferential; I try to get the professor to like me; I am nice to the professor”
Other-Schema: “The professor is a fair person; he likes to exchange pleasantries”
Interpersonal Scripts:
- *Food in Class Script:* “If the professor brings pizza or candy to class, then I join others in thanking the professor; I accept the food and consider it a mark of the professor’s kindness (and not bribery for high evaluations)”
- *Absence Script:* “If I email the professor before class about the reason for missing class, then the professor will email back confirmation; later in the week I attend office hours; if I show knowledge of the material, then the professor will be pleased and will not penalize my absence”
- *Helping Script:* “After class, I walk around the room to help the professor gather spare/discarded handouts; if I help close up the room, the professor will be thankful and interpret this as genuine assistance (and not a shameless attempt for a higher grade)”
- Etc… [more scripts]

In short, a relational schema is a complex knowledge structure which enables a person to understand how to interpret and conduct interactions with that person. We have many relational schemas. In order to more efficiently store these schemas in our minds, they exist at different levels of generality (Abelson 1981). Very general schemas optimize brain space: this is when we use a single schema for a variety of people (e.g. a generic schema when interacting with waiters at restaurants). Very specific schemas allow more complex interactions with a person (e.g. get to know particular waiters and interact in a unique way with each, developing unique relational schemas for each)

As with other schemas, relational schemas help a person attend to information (Taylor, Crocker, and Dagostino 1978). A relational schema provides a "lens" through which we notice information while interacting with another person: Schema-relevant behavior is best recognized and remembered, and behavior irrelevant to the schema is less likely to be attended to (it's not noticed; it falls under the proverbial "radar"). Once information is attended to, relational schemas also help us process that information (Carlston 1980). In particular, scripts enable a person to understand the meaning of another person's behavior, know what to do next, and what to expect of the other person; once a person's behavior can be recognized as being a part of a particular script, we now know "what's supposed to happen next", or what scene we are enacting.

And finally, relational schemas structure retention and recall of information (Davis and Todd 1985; Schustack and Anderson 1979): Schema-consistent behavior is remembered more than moderately schema-inconsistent behavior. In the above example, the student will accurately remember the instances where he did help pick up handouts after class, he did help the professor close up the room, and the professor did seem thankful, because those instances fit the Helping Script perfectly. The student is less likely to accurately remember the instances that are somewhat but not completely consistent, such as times when the student didn't help pick up handouts, but he did help close up the room. In fact, the schema is likely to bias his memory, making him think he *did* pick up handouts, even though he didn't actually do it that time – in this way, schemas influence memory and recall. However, very schema-inconsistent behavior is remembered accurately and vividly, because the unexpectedness of the behavior triggers heightened attention to the behavior. A day when the professor sneers at the student and accuses him of being a grade grubber, for example, would be quite vividly remembered (and may lead to subsequent change of the schema).

Research consistently shows that relational schemas can contain widely held shared understandings – understandings which are culturally-dependent. There is a lot of commonality in how friendship schemas are constructed within a particular cultural setting (Davis and Todd 1985), for example. Further, studies have found that the elements that make up schemas are varied in their importance: Some scripts are considered critical to the schema, while others are peripheral, and people generally agree on which aspects are critical versus peripheral (Fehr 2004; Fehr 2005), again highlighting the role of shared culture.

RELATIONAL SCHEMA DEVELOPMENT – THEORY AND HYPOTHESES

Each person has very many relational schemas, and these schemas are learned over time. As the person interacts with others, he or she applies currently known schemas. But if the other person's behavior does not match the schema – triggering attention to very schema-inconsistent behavior – he or she must adapt by either developing a new schema or altering/adding to the old one (Crocker, Fiske, and Taylor 1984). As a person is exposed to new social environments, such as a new workplace, he or she learns through others what is valued in interaction and what are typical patterns of behavior and their meaning. From these shared understandings, the person develops new relational schemas, internalizing what he or she has learned. Therefore, one's repertoire of relational schemas is developed both by adding new relational schemas one learns from new social situations and by adapting relational schemas to include greater and richer scripts for interpersonal behavior.

For example, a new intern may realize that getting to know one's peers socially will develop stronger work relations, and have an idea of how to do so (let's call it an "inviting others out for a drink" script). After engaging in such socialization over a length of time, though, the intern would learn that in this organization, certain ways of suggesting socialization are better or more accepted than others, and that different people require different approaches. As a result, the intern's relational schema for interaction with his or her coworkers develops greater variety – it includes more specific behaviors within the scripts (e.g. exactly how to suggest going out for drinks) and also has a greater number of scripts (suggesting one kind of socialization versus another according to the situation). In fact, this process may lead to creating new relational schemas: As the intern develops a pattern of interacting with some coworkers differently while socializing, he or she develops a different way of relating with them than others.

This process of developing a greater variety of relational schemas happens at both conscious and unconscious levels. While the new intern above may have consciously tried to figure out how best to interact with specific peers, resulting in him thoughtfully realizing that he ought to interact differently with each, this need not have been the case. Much of social behavior is unconscious and habitual; we do not "think" about how to act, but just act (Bargh and Chartrand 1999). In fact, relational schemas operate below the level of consciousness, guiding our decision about what to do – matching appropriate behavior to the situation – without "thinking" about it. Over time, the development of new relational schemas can occur similarly without conscious reflection. It may just happen one day that a colleague suggests an afternoon walk, which results in a rewarding interaction. This leads to a repeat occurrence, and then another. Gradually, unconsciously, and unintentionally, a new interpersonal script (going on walks) becomes a feature of one's relationship with that person. This new script then causes a new relational schema to be formed, since the way that one relates to this colleague is now different from the way one relates to other colleagues due to the new practice of walking together. Thus, increasing one's repertoire of schemas can happen consciously or unconsciously.

Determinants of Variety of Relational Schemas (Social experience and exposure)

However, not everyone has developed relational schemas to the same extent. When a person has relational schemas that are fewer in number, but apply to multiple people, these relational schemas are more generic. This means the person cognitively "lumps" relational alters into the same relational bucket, treating those relationships as being the same. For example, during the course of one interview, the interviewee paused and reflected on what he'd said thus far. He said with some surprise, "You know, this is kind of hard [to describe how I interact with each person differently]. I kind of say the same thing about everyone, don't I?" In his mind, his daily interactions with his colleagues were all very similar, allowing him to easily interact with many people. To some extent, we all use some amount of cognitive lumping, which allows us to simplify the mental models required for social interaction with a wide variety of people. Cognitive lumping is consistent with the "cognitive miser" perspective (Fiske and Taylor 1984). The cognitive miser perspective emphasizes that we exist in enormously information-rich environments, and thus in order to be able to make sense of our environments, we must selectively attend to that information, using the least amount of mental resources possible. Our use of stereotypes (Macrae and Bodenhausen 2000) is an example of the effect of cognitive miserliness. When we stereotype others, we perceive them as being in a category (based on race, age, etc), and then base our expectations and evaluations of them on our perceptions of the category, rather than the unique properties of the individual (e.g. Quadflieg and Macrae 2011). Cognitive lumping of relationships is like stereotyping at a relational level. Rather than treating each relationship as having varied unique properties, instead relationships are treated as members of a group – a set of relationships that use a single relational schema.

However, a tension exists. Being a cognitive miser may make interactions easier to engage in, in the sense that having a lower variety of schemas (cognitive lumping) enables a person to interact with a wider range of people using fewer cognitive resources (Abelson 1981). But being a cognitive miser is not necessarily adaptive: When one treats different relationships the same, this reduces the opportunity to develop more specific patterns of interaction with some of those people, as compared to others, which can limit the relational resources one has access to. For instance, different relational partners may be more or less willing to provide help, emotional support, advice, information, and fun. Similarly, relating to one person may require a different set of behaviors than another person, due to differences between those people's expectations about appropriate interpersonal behavior. However, cognitive lumping – treating those two relationships the same – would cause one to overlook the differing expectations and available resources within each relationship. Thus, having a greater variety of schemas enables a person to better adapt to the needs of each relationship.

Given this tension, I suggest that two processes operate to shape how varied a person's relational schemas become. First, when cognitive overload is not a constraining factor, for instance when a person is new in an organization and therefore has a low variety of relational schemas in that context, the person will develop relational schemas to the extent that his or her ongoing social experience provides the opportunity to get exposure to new people and situations. In general, people seek to be adaptive in their social environments: As people interact, they develop a shared understanding of "what we are doing now," framing the scene (Goffman 1974), which makes intelligible each person's actions. Actions which do not match this understanding are felt as jarring (Garfinkel 1967) or are ignored or contested (Goffman 1959). That is, we strive to understand and match the social expectations of any given situation. This means that cognitive lumping will decrease with increases in social experience, since greater social exposure will increase the variety of social interaction patterns a person has internalized. However, when the variety of relational schemas developed becomes high, cognitive overload becomes a constraining factor, overriding the need to become more adaptive. Then, cognitive lumping will increase with increases in social experience, because new experiences will be integrated into pre-existing relational schemas. In other words, new experiences and new relationships will be treated as being the same as old ones, in order to simplify the process of perceiving and reacting to social interactions. Summarizing these expectations, I hypothesize a curvilinear effect of social experience and the variety of one's relational schemas.

Yet there are several ways to characterize how much social experience a person has in an environment. How embedded a person is in social networks is one indicator. The number of contacts a person has reflects their embeddedness in an environment, and indicates how much exposure a person has had within a social group. The more people a person knows, the greater the opportunity and need to learn diverse ways of interacting.

However, knowing very many people can trigger cognitive overload, causing one to begin to lump relationships into the same mental model (schema).

Hypothesis 1: Number of contacts has a curvilinear relationship with variety of relational schemas, such that at low levels of number of contacts, increases in number of contacts are related to increases in variety of relational schemas. At high levels of number of contacts, increases in number of contacts are related to decreases in variety of relational schemas (more cognitive lumping).

Another indicator of such social exposure is how many people a person interacts with on a day-to-day basis. Note that how many people one knows (number of contacts) is not necessarily the same as the number of people one interacts with regularly. One can interact with people one barely knows. These would be more limited interactions, but they are still interactions which must be adaptively navigated. Also, one might not interact often with some people one knows, effectively reducing the amount of daily social exposure. Thus, if the amount of cognitive lumping is triggered by the mental stress of managing daily interactions with others, then the number of people one actually interacts with on a daily basis should determine how much cognitive lumping occurs.

Hypothesis 2: How many people one interacts with on a daily basis (average daily interaction partners) has a curvilinear relationship with variety of relational schemas, such that at low levels of average daily interaction partners, increases in average daily interaction partners are related to increases in variety of relational schemas. At high levels of average daily interaction partners, increases in average daily interaction partners are related to decreases in variety of relational schemas (more cognitive lumping).

On the other hand, the simple number of people one interacts with on a daily basis may not reflect the complexity of one's social exposure. With some relational partners, a person may need to engage in only one form of behavior, such as accepting new mail or scheduling an appointment. But for other relational partners, one may need to engage in multiple forms of behavior, such as working on a project, scheduling meetings, reviewing others' work, and chatting about social events. The greater the variety of activities one must engage in with others is a form of social exposure which should increase the relational schemas that one develops (again, up until cognitive overload is triggered). While not ideal, the amount of time one spends interacting with others may be a proxy for how many different forms of interaction one must engage in with others. The more time a person spends interacting during the day, the more likely the person is engaging in a variety of different activities with others. Spending more time interacting per day should bring more social exposure (decreasing cognitive lumping), but when one already spends a great amount of time interacting per day, increases in time spent in interaction should lead one to increase cognitive lumping.

Hypothesis 3: Average daily interaction minutes has a curvilinear relationship with variety of relational schemas, such that at low levels of average daily interaction minutes, increases in average daily interaction minutes are related to increases in variety of relational schemas. At high levels of average daily interaction minutes, increases in average daily interaction minutes are related to decreases in variety of relational schemas (more cognitive lumping).

And finally, a person's accumulated experience in an environment must be considered. Each of the previous hypotheses relate to a person's ongoing experience, i.e. the present levels of daily interaction. Yet the schemas that people hold can reflect past social experience as well. For instance, the longer two people have known each other, the more likely they are to have engaged in multiple forms of interaction (producing greater social experience), even if the amount of time they spend interacting remains the same. An example would be when work patterns change: Prior exposure to each other might have involved collaborating on a project, and subsequent exposure to each other might involve purely social contact after the project is done. The longer a person has been in an environment (the longer his or her tenure), the more likely the person has experienced a greater variety of social experiences, even if the size of his or her network or time spent interacting remains the same. This increase in social experience should at first increase the variety of relational schemas a person develops, but at high levels of tenure, the need to simplify mental models for interaction create cognitive lumping.

Hypothesis 4: Tenure has a curvilinear relationship with variety of relational schemas, such that at low levels of tenure, increases in tenure are related to increases in variety of relational schemas. At high levels of tenure, increases in tenure are related to decreases in variety of relational schemas (more cognitive lumping).

Determinants of Variety of Relational Schemas (Social information)

Relational schema development should also be enhanced when people learn about others' relationships, not just through their own experiences. This too happens via social interaction (e.g. gossip). When we learn about others' interactions and relationships, we learn vicariously, customizing our schemas to integrate others' experiences, so that they may be ready for our use on the occasion we need it. The more embedded a person is within a social environment, the more he or she learns about others' relationships: People who are central in networks receive more social information (Casciaro 1998), which over time should result in more relational schema development. For example, hearing gossip about John & Denise's love-hate relationship results in developing a new relational schema that includes tension (fighting scripts) with friendship (affection scripts). One form of centrality has already been hypothesized – the number of contacts one has both increases one's own direct social exposure, and also increases the amount of indirect information one receives from others. In addition, another form of centrality that is relevant is structural holes, which captures how much the person receives information indirectly from others (Burt 1992; Burt 2004). The more a person's direct contacts themselves are not connected to each other (higher in structural holes), the higher the person's chances of receiving greater amounts of diverse information about others in the social environment.

Hypothesis 5: The number of structural holes spanned by a person has a curvilinear relationship with variety of relational schemas, such that at low levels of structural holes, increases in structural holes are related to increases in variety of relational schemas. At high levels of structural holes, increases in structural holes are related to decreases in variety of relational schemas (more cognitive lumping).

There are other ways in which a person would learn of others' relationships. In some environments, a person's position can lead to enhanced information about others. For instance, in a work environment, part of a manager's role is explicitly to develop relationships with others (Gosling and Mintzberg 2003; Ibarra and Hunter 2007) and to monitor others' work relations. Additionally, when managers interact with other managers to coordinate work, part of their interaction may involve directly discussing others' relationships: for instance, when discussing which subordinates to appoint to teams, particularly when difficult or even toxic relationships (Frost 2003) impede the ability of some employees to work together. One manager who was interviewed provided an example of this type of attention to others' relationships: He described how some of his subordinates had difficulty interacting with certain others in the department, due to misunderstandings and lack of communication. He said, "I have to be the mediator of that. So I have to consciously say, 'Person X in my group go sit with Person Y over there, and take 'em through what you're planning to do, so that they're comfortable and they can give you pointers on it.' And then behind the scenes I'll have to go to their manager – Person Y's manager – and say, 'Here is what I am doing with Person X in my group and Person Y in your group, so you know that we're trying to make this work." Because of this manager's effort as well as the other manager's effort, he was able to help repair the relationship between the two subordinates. Other managers at ManuCorp similarly discussed the need to pay attention to their subordinates' interactions, being willing to mediate when needed, with the goal of encouraging a positive and productive work atmosphere. Holding all else equal, this should make managers both more sensitive to relational information and more likely to develop varied relational schemas.

Hypothesis 6a: Management position is related to higher variety of relational schemas (due to higher levels of social information required by managerial jobs).

Yet can be argued that managers, having more power, are less sensitive to others, due to the social distance created by their position. People who have power are more likely to objectify others, perceiving others only in ways that are relevant to their instrumental usefulness, and as a result ignoring other qualities of the person (Gruenfeld, Inesi, Magee, and Galinsky 2008). In general, powerful people are less likely to listen to others' advice (Tost, Gino, and Larrick 2012), and are less likely to attend to information that disconfirms their existing views (Brinol, Petty, Valle, and Rucker 2007). As a result, people who have power should be less attentive to their social environments, making them less perceptive of others' relationships. Accordingly, Simpson, Markovsky, and Steketee (2011) found that people primed with high power tend to have less accurate network perceptions than those primed with low power, since those with high power are less motivated to attend relational information. Thus, while management position might provide a person with greater *access* to social information, it may paradoxically make them less able to process that information.

Hypothesis 6b: Management position is related to lower variety of relational schemas (due to social distance between management and subordinates and tendency of those in power to ignore others).

Outcome of Variety of Relational Schemas

Thus far it has been argued that developing a greater variety of relational schemas is socially adaptive. A person who has a greater variety of relational schemas has found different ways of relating to different relational partners. If distinguishing between relations in this way is adaptive (and not counterproductive), then it should increase a person's ability to understand his or her social relations. In other words, by mentally distinguishing between relations (not treating them the same), a person can better recognize when relationships change, becoming stronger or weaker. Those who have higher variety of relational schemas should have higher relational acumen, the ability to accurately judge the strength of one's relationships.

Hypothesis 7: Variety of relational schemas has a positive relationship with relational acumen.

Methods

Data

This study takes advantage of data in each of the three stages of data collection at ManuCorp. This includes: the contact network and demographic data at Time 1 (n=33), interaction data at Time 2 (n=34), recorded interview data at Time 3 (n=24), and personality data at Time 3 (n=32). Note that the recorded and transcribed interview data provide qualitative data from each participant on his or her relationships with others in the department. I asked each participant to describe the details of his or her histories and interactions with each other person in the department. I asked, "Tell me the story of how you got to know each person, and how that relationship evolved over time." I also asked "Describe a typical interaction with that person" in each case. (For more details, please refer to Chapter II: Site and Data.)

The literature on schemas (particularly relational schemas) and scripts has a wide variety of methodologies for measuring these mental constructs. Baldwin (1992, p.471-472) reviews the variety of methods used in cognitive psychology to measure relational schemas particularly, including self-report, memory and response bias measures, and observation. Self-report methods include asking study subjects to rate the occurrence of certain patterns of behavior in their relationships (Christensen 1987), and asking participants to rate the importance of certain features of relationships (Hassebrauck 1997). Measures of schemas can also be obtained by using memory tests, for example by asking participants to read and then later recall a scenario involving interpersonal interaction. Discrepancies in memory (the difference between the actual scenario and the recalled version) indicate the content of relational schemas, since relational schemas structure the recall of events (Planalp 1985). In a similar vein, the use of the Implicit Assessment Test (IAT) can be used to test whether certain behaviors or perceptions are part of schemas; by measuring response time in categorizing stimuli, such as "Me" and "Collaborative", the IAT measures how closely certain items are associated in one's mental schemas (Srivastava and Banaji 2011).

In the sociological study of scripts and schemas, methods have also included ethnographic observation, inductive interviews, and surveys. Wherry (2012) demonstrates how shared scripts are identifiable via ethnography, by examining the performance of economic behavior and the meaning ascribed to that behavior by participants. Harding (2009) has also used unstructured interviews to elicit scripts; by asking minority urban boys to describe how they interact with others in the neighborhood and their strategies for dealing with violence, girls, school, and other topics. Surveys can also be used, by asking respondents to indicate which option most closely resembles how they act or think about a problem (Harding 2007; Vaisey 2009)

Thus, there is no single – or even dominant – method for measuring schemas and scripts. Instead, the method must be suited to the needs of the research question. In many cases, the research question involves testing whether certain schemas or scripts are used by people, in which case a fixed-choice survey item can be appropriate. For instance, in Vaisey's study of moral decision-making, his goal was to identify the most salient or dominant schema for moral decision-making held by each person, and so a survey question which provided a fixed list of various decision-making approaches (e.g. "Do what would make you feel happy", "Do what would help you to get ahead") worked well. Similarly, Harding's (2007) study of youth's relationship scripts utilized survey items asking respondents whether they engaged in various behaviors with partners such as "We would hold hands" and "I would meet my partner's parents". Srivastava and Banaji (2011), however, point out that when doing research in a setting where the culture places positive value on a particular schema or set of scripts, self-report measures can be biased. In their case, they use an IAT test to measure collaborative self-schemas and show that in an organization that values collaboration, people over-report how collaborative they are on surveys.

This study differs from many of the preceding studies of schemas because the goal is not to test for the use of any *particular* schema, but rather to explore the extent of schema development (the variety of relational schemas). Therefore, using a fixed-choice survey item, or even an IAT or other response or memory test, is inappropriate. The methods must not presume the existence of any particular schema, but instead take an exploratory approach and discover what schemas are in use by whom. Therefore, the approach adopted here is to ask each participant about each of their relationships, using the interview data to code scripts and schemas inductively.

However, there is a concern that interviewees' sense-making about their relationships may or may not reflect the actual schemas they hold. In dual-process models of decision-making (e.g. Haidt 2001), the conscious sense-making that we engage in is a justification mechanism – it's a post-hoc rationalization that may or may not correspond to future action. By contrast, it is the unconscious mind (which utilizes schematic decision-making) which provides the motive for action in most situations. This dual-process mechanism applies generally to all modes of decision-making, and is relevant here because interpersonal interaction necessarily involves decision-making, i.e. what to do next and how to interact with the person. The relational schemas that we hold are primarily in the unconscious part of this dual-process. Thus, the methodological choices in measuring schemas via self-report must take care to distinguish between conscious sense-making (justification of interpersonal action) and the less conscious relational schemas (motivators of interpersonal action). Vaisey (2009) shows that measures which focus on routine action (i.e. making a choice about how to proceed) are better assessments of schemas than measures which focus on reasoning (i.e. providing a reason for action), since when presented with a routine choice the unconscious mind is activated.

Interviews of employees at ManuCorp included discussion of both interviewees' sensemaking about their relationships (e.g. "we're friends") as well as descriptions of action/choices (e.g. "he got me a birthday present"). In order to capture most closely the underlying relational schemas that each interviewee holds, the coding of transcripts (described in detail in the next section) focused only on action statements – descriptions of behavior the person has or would engage in with others. Action statements arose most in response to the prompt "Describe a typical interaction with that person," but also arose throughout interviewees' narratives of their relationship histories. These action statements are used as indicators of the scripts which comprise relational schemas[4]. In sum, given that the goal of this study is to identify the variety of schemas people have, the methodology most appropriate is a qualitative interview where schemas are inductively determined, using interviewees' reports of behaviors/action with others. While response bias cannot be ruled out, there is no reason to believe that interviewees' responses were biased towards disclosing greater or lesser variation in their interactions with others.

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[4] Note that since relational schemas are made up of three elements (self-schema, other-schema, and interpersonal scripts), focusing only on variation in scripts simplifies the analysis. In future research, assessing variation in the self-schema and other-schema components of relational schemas may be useful as well.

Measures

Dependent Variables

Variety of Relational Schemas: Number of Schemas, Number of Scripts, and Generality of Scripts

Since relational schemas are complex mental structures, no single variable can capture how varied or generic a person's schemas are. Instead, there are at least three ways of characterizing the variety of a person's relational schemas, and each of these are used as dependent variables. Each relational schema a person has contains multiple interpersonal scripts, and is used by a person to relate to one or more other individuals. First, relational schemas have greater variety if there are simply more of them (*Number of Schemas)*, holding constant the number of individuals one relates to: For example, having five different relational schemas to relate to five individuals (one schema per person) means greater variety and specificity than having only one relational schema that is used for all five individuals. Second, relational schemas are more varied if they have more contents; in other words, if more scripts are utilized overall, across schemas (*Number of Scripts)*. Third, relational schemas are more varied if the particular scripts used are more distinctive – they are not included in multiple schemas (*Generality of Scripts)*[5]. Below is a description of how the scripts and schemas were identified, followed by more precise definitions of each of the three variety of relational schemas variables.

<u>Identifying Scripts</u>

Each person's comments about each of their colleagues were coded for scripts, which are patterns of behavior. While scripts can be quite detailed in a person's mind, it was

[5] While it would be more logical to identify this variable as the specificity of scripts, the calculation of the measure (as described later) is most conducive to the reverse concept. Therefore it is called generality of scripts.

not possible to elicit all their details in the interviews; instead, interviewees referenced scripts via general labels or conventions, such as "I would see him in meetings" or "we'd go to lunch together". Presumably, the interviewee had a complete script for seeing a person in meetings, which might include how to greet the person, how to interact during the meeting, and how to conclude the interaction – but this level of description is not a typical or "natural" way to discuss interaction in conversation. Instead, scripts are often identified via general labels.

The way interviewees reference scripts via labels is demonstrated by the following quote:

> Joy says "I like Ashley a lot and I have worked with her on some projects and stuff. Uh, so I like Ashley a lot and respect her a lot…. her husband's neat, too, and we've done stuff where we've gone to baseball games or office stuff after hours, and they're usually at that stuff and fun people to be with."

In the above, the coded scripts are: "working on projects" "going to baseball games" "office stuff after hours" "interacting with spouse" – phrases which capture as closely as possible the distinctions that Joy herself identified between forms of interaction with Ashley and others. Because relational schemas are specific to each person, I developed codes for scripts reflecting only what *that* person said about his or her interactions.[6] I purposely refrained from developing general script categories across interviewees or using my own sense of how to group together similar patterns of behavior. To do this, I looked to the distinctions that the interviewees themselves made between interactions: For example, Joy talks about "going to baseball games" and "office stuff after hours" with Ashley, but only talks specifically about "going to picnics" with John. This reflects how Joy has developed her relational schemas – she has made a distinction between relationships, indicating that different scripts are applicable to different people. See Table 1, below, for an

[6] This was achieved by having a separate Atlas.ti file for coding each interview transcript.

example taken from one interviewee, Dan. The table lists all of the twenty-four scripts mentioned by Dan, along with sample quotes and which people for whom each script is applicable. Some scripts are used for multiple people, while other scripts are used just for one person.

While interviewees often referred to different forms of interactions via labels, such as in Joy's example, other times interviewees recounted more specific actions in context, providing richer detail about interactions. For instance, the first script identified for Dan in Table 1 has the quote "And she accepts mistakes, and does a great job, um, helping you correct those without making you feel like a fool." Here, Dan is recounting a single interaction, in which Laura brought to Dan's attention his mistake (first behavior) and helped him correct it (second behavior), with the outcome of him not feeling like a fool. And in the subsequent quote in the table Dan elaborates further, even including the specific language Laura used. In coding these more elaborate descriptions, I sought to identify the sequence of behaviors which comprise an interaction episode (again, staying as close as possible to the distinctions interviewees made between interactions), rather than discrete behaviors. The code "accepting mistakes and respecting each other" summarizes the sequence of behaviors Dan described as a single interaction, although in each quote several specific actions were mentioned. This way of coding scripts most closely resembles the definition of a script as a pattern of behavior, or a series of actions which happen in sequence.

TABLE 1: CODED SCRIPTS AND QUOTES FROM DAN'S INTERVIEW

Script	Sample Quotes	People Script Applies to
accepting mistakes and respecting each other	"And she accepts mistakes, and does a great job, um, helping you correct those without making you feel like a fool." "She says 'no, you're doing something wrong' and she went over it with me. And you know, she made, just the way she explained it was, was well, she did it well. And then didn't make me feel like an idiot. And then she says, 'I did the same thing' and, you know, I don't know whether she did or she didn't. But it didn't matter."	Laura
answering questions and helping	"Gina asks me a lot of questions, and I go, and I help her quite a bit. " "Diane and I were working, she was working on a project with [X topic][7], and she would come to me, and her and I would discuss… She didn't understand how [X topic] was generated, how it um moved through the plant..."	Gina & Diane
confiding in each other	"Laura I can confide in. She's the only one here I would. You know, if I'm feeling bad about something, or somebody says something to me to hurt my feelings or something like that, I can confide in her. "	Laura
getting along and seeing eye to eye	[After describing similar living situations] " so we kinda get into the same things. Just evolved from there, and you know. Just get along and see things eye to eye. Just the way it is, I don't know."	Laura
getting angry with me	[Part of a long story on a misunderstanding] " I didn't have anything to do with it, so Penny got upset at me for what she thought, perceived something to happen and nothing happened."	Penny
helping me out	"And uh, he was pretty instrumental in giving me a heads up that there was an opening here. So, Travis said 'hey, I think you should, you know, take a look at this opportunity.' He called me up and I said 'Travis I don't know--- Shit I don't know how to do this. 'I've only been doing this stuff for three years,' and he said, 'No, do it'." And so I did it, and he I think he was instrumental in, helping me out...[to get the job]"	Travis

[7] Topic names have been removed to preserve individual and organizational anonymity.

infrequently talking	"Brendon, he's three doors down, so I talk to him... sporadically." "Derrick, hardly ever [talked to him]. I do more now than we used to... "	Brendon & Derrick
interact at meetings	"I got moved over to this side of the office, in a different, totally different group, um, you know, we were in the same meetings together, we were, we're all interacting via those meetings or just passing each other." "Jack is James' boss, my supervisor's boss. So we [all] interact via occasional meetings."	Winny, Jack, & James
interacting as a result of 3rd person	"Alex and Travis are pretty tight. And so Travis was behind me, in my old desk, and um, so I would interact with Alex that way."	Alex
interacting for project/plant	"Harry, I work with him on one of the plants. " "Sandra and I are working together on a plant, currently." "Don and I worked together on a plant." "So, Kevin and I were working on a project at one of my plants. " etc	Winny, Lara, Harry, Sandra, Kevin, Roseanne, William, & Don
not talking when passing by	" And I will walk by, and I won't say hi, by the time I'm walking by... [because] she faces the other way. (chuckle)... by the time she turns around, I'm gone. She doesn't know who was... what the hell [happened]...(mumbles). She might say hi to me, I have no clue. (laughter)"	Sally
seeing each other outside of work & with spouse	"And I also see Laura, her and her husband, outside of work. ... You know, once or twice a year, or something like that."	Laura
sharing knowledge	"So now James, my supervisor, put her with me, to show her some different things. "	Winny
taking a trip and getting to know each other	"And then her and I took a trip to Louisville together, to um, and that's when it really got to know her, "	Laura
talk about personal stuff while working together	"I mean when you have to work together on a project, you know, inevitably personal stuff comes up, and you just talk..."	Winny

talking about [Y topic]	"The guy's just, he's just, he knows everything there is to know about [Y topic]. He helps [external parties] out actually, so he's just a bright guy. So, I was finishing up a [Y topic project] at the time, so that's why I talked to Hector a lot." " Gordon is another [Y topic] person, who I used to go to quite a bit, when I was working on those…"	Hector & Gordon
talking about kids to not have hard feelings	"And I'm not gonna make it an unpleasant experience. She's not gonna make it an unpleasant experience. So we talk about [our] kids, and what the kids do. Stuff like that. Just over time, it's just, it's gotten better. And, I'm sure it will. I have no hard feelings about her, so. "	Penny
talking about mutual opinions	"Sharon... her and I have mutual opinions on certain things... within the office. As far as um, not about 'managers' but how things are managed. So, you know, ...we'd like see things differently, but you know we're not managers. So, it's just the way it is. (chuckle) We think it'd be better, but, you know. So we talk about that stuff, you know."	Sharon
talking about office activities	"So, her and I talk a lot about basically ... activities outside of the office er... [well it has to do with] the office but we schedule things together. "	Sharon
talking all the time	"Jane, of course, I talk to Jane all the time"	Jane
talking and getting close	"So her and I have become a lot closer, her and I talk a lot, about different things, and, that's been a significant change." … " I'm able to look over and see she's sad, and see... so I'd go over and talk with her and things like that."	Erin
talking in the hall	"He passes by my desk, and he's one of these people, like I am. I don't pass by somebody's desk without saying hi. So I just say hi. Always go, 'hey, how's it going?'" "Chris, he just walks around and talks to everybody"	Victor & Chris
took me under her wing	" I was given Laura's some of her assignments, and she was moved over to a new area. So Laura, you know, kind of took me under her wing and uh, kind of trained me, basically"	Laura
working closely together	"I work closely with Winny, who is, she's relatively new." "James…. And Jack as well... I work with them very closely." "And Sharon too. Her and I work closely together, on our Fun Team, in other words, we're the ones who organize the office activities and things like that, so." "I've known Travis for fifteen years, him and I worked together at a plant. .. So we had to work very closely together, "	Winny, Jack, Sharon, Travis, & James

Identifying Schemas

Each combination of scripts represents a different relational schema. Using the prior example, suppose Joy talks about "working on projects" (and nothing else) with both Sherry and Tom. This means Joy applies the same relational schema to both Sherry and Tom. The combination of scripts Joy applies for Ashley ["working on projects", "going to baseball games", "office stuff after hours", and "interacting with spouse"] is a different relational schema from the one Joy applies to Sherry and Tom. Even though Joy employs one similar script ("working on projects") when interacting with all three people, Joy's schema for interactions with Ashley is broader. Sometimes interviewees said directly that their interactions with one person are the same as another person mentioned earlier, instead of repeating the particular scripts mentioned earlier. In this case, I coded the scripts mentioned earlier as being applicable to both people.

After identifying all the scripts a person mentions for each person, and then grouping the unique combinations of scripts, I identified the number of distinct relational schemas the person's interview provides evidence for. Table 2 shows Dan's relational schemas, identified from the scripts in Table 1. For example, Dan has one relational schema that he applies to seven different people, and it is composed of a single script: interacting for a project/plant. For all seven people, Dan's description of how he interacts with that person is a variant of "I work with him/her on a project." Dan chooses not to go into detail, for instance by giving the name of the project or what topics or activities were involved, because to him it's not relevant to describing their interaction: "working on a plant together" is the same form of interaction as far as he's concerned for each of these people, no matter which project/plant is involved. This example shows how relational schemas operate – in this case, Dan uses a single relational schema to guide his understanding of and participation in relationships with these seven people. By contrast, some of Dan's discussion of his interaction with other people *does* involve more details. For instance, Dan chooses to mention the specific plant (Louisville) that he worked with Laura on, and the added details he describes about that form of interaction (getting to know her) set that script apart from just "working on a plant together". Similarly, Dan's discussion about interactions with Hector and Gordon contain details about the specific topic that he talks to them about. This serves to set Dan's script for interacting with Hector and Gordon apart from the script he uses for the seven people mentioned earlier. In this way, I coded scripts and schemas by examining closely how the interviewee himself or herself made distinctions between interactions with people. Dan's interview data includes fifteen distinct relational schemas.

TABLE 2: CODED SCHEMAS AND SCRIPTS FROM DAN'S INTERVIEW

Relational Schema #	Scripts	People Schema Applies To
1	interacting for project/plant	Lara, Harry, Sandra, Kevin, Roseanne, William, & Don
2	interact at meetings	Jack & James
	working closely together	
3	answering questions and helping	Gina & Diane
4	talking in the hall	Victor & Chris
5	infrequently talking	Brendon & Derrick
6	talking about [Y topic]	Hector & Gordon
7	not talking when passing by	Sally
8	interacting as a result of 3rd person	Alex
9	getting angry with me	Penny
	talking about kids to not have hard feelings	
10	accepting mistakes and respecting each other	Laura
	confiding in each other	
	getting along and seeing eye to eye	
	seeing each other outside of work & with spouse	
	taking a trip and getting to know each other	

	took me under her wing	
11	interact at meetings	Winny
	interacting for project	
	sharing knowledge	
	talk about personal stuff while working together	
	working closely together	
12	talking all the time	Jane
13	talking about mutual opinions	Sharon
	talking about office activities	
	working closely together	
14	helping me out	Travis
	working closely together	
15	talking and getting close	Erin

Note that the schemas and scripts listed for Dan are specific to Dan only; for each other interviewee, the coding of scripts and schemas starts anew, and is not affected by Dan's scripts or anyone else's. By coding relational schemas using this method – first coding scripts from interviewees' statements of interactions with others, and next by identifying which combinations of scripts were applied to one or more colleagues – the schemas identified are inductive and least biased by researcher expectations of the content of schemas. In other words, determination of each interviewee's schemas remains as close as possible to how *that specific interviewee* views his or her relationships, regardless of the content and variety of other interviewees' and the researcher's own schemas. This approach can be used in any setting, although the disadvantage of measuring schemas in this way is the effort required to inductively code each interviewee's scripts.

Number of Schemas: The number of distinct schemas a person has is one indicator of the variety of a person's schemas. However, one would expect error in some of the schemas identified using the above method. Using that method, any single difference, no matter how small, in the scripts mentioned for different people would cause the creation of a separate schema. This also means that if an interviewee neglected to mention some shared scripts, it could cause more relational schemas to be constructed than appropriate. Consider Dan's schemas 2 and 14. Both of these schemas have two scripts, one of which is shared ("working closely together"). What if Dan forgot to mention that he interacts with Travis in meetings, and that Jack and James both help him out? If that were the case, then Dan's relational schemas for interacting with Jack, James, and Travis would actually be a single schema, but erroneously considered to be different schemas here.

To correct for this problem, I created another assessment of relational schemas, based on factor analysis of each person's scripts. This method assumes that "true" relational schemas are latent constructs based on combinations of the scripts mentioned. For each person, I created a dataset with the person's scripts as the set of variables and with each relational partner discussed as an observation/row. The data indicate which scripts apply to which person. For example, in Dan's dataset, the observation/row for Erin has "1" in the variable "talking and getting close", and "0" in all other variables. I then conducted an exploratory factor analysis on each person's data. The number of retained factors in the analysis is the number of (latent) relational schemas for that person. This number was quite highly correlated ($r=0.97$) with the number of schemas I identified using the more manual method described earlier, providing validation for the use of factor analysis. However, the number of schemas identified via factor analysis should be a more accurate measure, since it is less sensitive to small variations in the scripts mentioned for each person. Accordingly, the exploratory factor analysis grouped together more schemas, resulting in an average of four fewer schemas than the prior method. Thus, Number of Schemas is defined as the number of retained factors in an exploratory factor analysis of each person's scripts.

Number of Scripts: The second way to characterize how varied a person's relational schemas are is to measure the distinct scripts the person employs. This is a simple count of the scripts, as identified above. (In Dan's case, there are twenty-four scripts.) This measure essentially captures how complex the relational schemas are.

Generality of Scripts: The third way to assess variety of relational schemas is to compare more directly the contents of the schemas (scripts). While distinct combinations of scripts indicate distinct relational schemas, it is also true that some scripts can be used across multiple schemas. (E.g., in Dan's case, "working closely together" appears in four different schemas.) How specific or general a person's scripts are across relational partners indicates how much he or she mentally "treats everyone the same". Cronbach's alpha, a measure of reliability, assesses how similar variables are; the higher the intercorrelation of the variables, the higher the Cronbach's alpha will be. Using Cronbach's alpha here, it essentially measures how similarly a person treats each of his or her relational partners, by applying scripts in the same away across people. For each person, I created another separate dataset, this time with the relational partners as variables and the set of scripts as observations/rows. (In this version of Dan's dataset, the observation for the script "talking and getting close" has a "1" in the column for Erin, and "0" in all other columns, since he didn't use that script for anyone else.) Cronbach's alpha is sensitive to the number of variables included – in this case the number of people each interviewee had scripts for – so it is important that each person's dataset have the same number of variables. However, not all interviewees had scripts for every single other person in the department. Thus, I added one extra "dummy script" in each dataset, with values of "1" for every person in the department. This ensured that the resulting measure would be comparable across people. The Cronbach's alpha for each person measures the degree to which scripts are applied more generically across relational partners (*Generality of Scripts)*. Since generality of scripts is the opposite of variety of relational schemas, hypothesis testing involves reversing the predicted direction of variable coefficients. This variable is multiplied by 100; theoretically, it can range from 0 to 100.

Relational Acumen: The variety of relational schemas is hypothesized to affect how accurately people assess the strength of their relationships. Consistent with the network perception accuracy literature (Casciaro 1998; Krackhardt 1990), I measure accuracy as the consistency between what an individual reports about his or her relationships with others and what others report about their relationships with the individual. Thus, relational acumen – or accuracy of perception of relationship strength – for each person is the correlation between their ratings of the strength of their relationships with each other person and others' ratings of the strength of their relationships with the focal person. Relationship strength ratings were obtained during the interviews. Each person was presented with a full list of the department members, and was asked to rate relationship strength with each other person on a scale of zero to five, where zero = no relationship; one = prefer to avoid[8]; two = very weak relationship; three = somewhat weak relationship; four = somewhat strong relationship; five = very strong relationship.

Independent Variables

Contact Network Degree: Degree centrality is the number of relational partners each person has in the contact network. In the social network survey at Time 1, each person was presented with a roster of the department and asked to indicate which people he or she does not know ("whom you interact with as a mere 'hello' or less"), with the remaining people

[8] Whether "prefer to avoid" should have a higher or lower value than "no relationship" is unclear. However, in this dataset, only one person chose to use the "prefer to avoid" category – and just for one relationship. Thus, the coding of "prefer to avoid" versus "no relationship" is inconsequential.

being people he or she does know. A relationship in this network exists when both people report that they have a relationship (they both do know each other more than a mere "hello").

Contact Network Constraint: The concept of structural holes is measured via the variable constraint (Burt 2004) in the contact network at Time 1. This assesses how redundant the person's contacts are, in the sense of providing access to the same third parties. A low level of constraint indicates that the person's network is high in structural holes, while a high level of constraint indicates that the person's network is low in structural holes.

Average Daily Interaction Partners: The average number of other people in the sample with whom each person interacted face-to-face (regardless of interaction length) per workday during the movement tracking period at Time 2. Note that a person who interacts with 10 people per day on average could be interacting with the same 10 people every day, or could be interacting with 10 different people each day.

Average Daily Interaction Hours: The average number of hours of interaction time per workday during the movement tracking period at Time 2. Even if a person was not present on a given day, that day is included in the average.

Management position: Coded zero for those who are not supervisors, and one for those who are supervisors.

Tenure: Length of time employed at ManuCorp, in years. While this measure does not capture how long each person has been in this particular department, the grand majority of interviewees reported during interviews that they knew people in this department many years before transferring in.

Controls

Personality: Agreeableness, extraversion, openness, and conscientiousness are measured via two items each from the Ten Item Personality Inventory (the fifth Big-5 personality variable, emotional stability, is not theoretically relevant). These are included as controls for two reasons. First, personality factors may influence interviewees' responses. For example, the more agreeable (pleasant or nice) an interviewee is, the more likely he or she may have been to volunteer information that is coded as scripts. Similarly, the higher a person rates on extraversion or openness (open to new experiences), the more likely he or she may have been to feel comfortable speaking at length about personal experiences, resulting in more coded scripts. Thus, including personality variables addresses potential biases in the interview process. The second reason to include personality variables is to allow for the fact that the variety of one's relational schemas may reflect cross-situational and time-invariant personal tendencies, which are typically assessed with these variables. Ultimately, this paper argues that it is one's history of social engagement which produces one's understanding of how to interact with others – hence, one's personal tendencies or "personality". However, since this study focuses on only one aspect of participants' lives (their work lives) for a limited period of time, it is wise to control for already-established personal tendencies.

Male: Women may be more likely to speak about relational topics and discuss interpersonal interaction. Also, being female may have created an increased sense of closeness between the women interviewed and myself, resulting in more discussion and more scripts coded. Either way, I control for the possible influence of sex.

RESULTS

Table 3 reports descriptive statistics and correlations among the variables. Since this dataset has a small number of observations, the results here should be taken as being suggestive, rather than strong evidence of support for hypotheses. Table 4 reports the results of negative binomial regression models predicting the number of schemas people have. The personality variables openness (one's openness to new experiences) and agreeableness (being pleasant, nice) are the most correlated with number of schemas, and while they are not significant in many of the models, their inclusion increases the R-squared values of models where they exist in combination with the independent variables. Extraversion and conscientiousness were also considered but dropped from the analysis since they did not improve model fit.

Hypothesis 1, that the number of contacts of a person has a curvilinear effect on their variety of relational schemas, is supported by Model 4. The first order effect of degree (number of contacts) is to increase the number of schemas. The degree squared term is significant and negative, which means that at higher levels of degree, the number of schemas decreases. Hypothesis 2, the curvilinear effect of a person's average daily interaction partners, is also supported: In Model 6, which tests Hypothesis 2, the main effect of average daily partners is positive and significant, and the squared term is negative and significant. At lower levels of average daily partners – when one interacts on a daily basis with fewer people – increases in daily partners increase the number of relational schemas one has. However, at higher levels of daily interaction partners, interacting with more people is associated with a decrease in the number of relational schemas.

By contrast, Hypothesis 3, that the time spent interacting has a curvilinear effect on the variety of relational schemas, is only marginally supported. There is stronger evidence for the main effect, that the greater the amount of time spent interacting with others, the higher the number of relational schemas one has. Next, Hypothesis 4 finds strong support in Model 10. As tenure in years increases from a low level, the number of schemas also increases; but at higher levels of tenure, increases in tenure produce decreases in the number of schemas. Hypothesis 5 refers to the effect of structural holes. Since constraint has the opposite meaning of structural holes, ordinarily hypothesis testing requires reversing the expected direction of hypotheses. However, in this study, since the structural holes hypothesis is curvilinear, the expected direction of the main and squared terms for constraint is the same as the hypothesis for structural holes. In any case, Hypothesis 5 has no support. And finally, Hypothesis 6a, that management position increases the variety of relational schemas, receives support. While the manager variable is not significant in all models, it is in the better models – all those that have a pseudo R-squared of 0.09 or higher. Overall, the models which provide the highest explanatory power are the two models with curvilinear effects of degree and tenure. Unfortunately, given low number of observations, it is not possible to test both curvilinear effects in the same model.

Table 5 shows results that are mostly similar in predicting the number of scripts. Both Hypothesis 1 (degree) and Hypothesis 4 (tenure) are supported. Hypothesis 2 (daily interaction partners) is only marginally supported (Model 6). Hypothesis 3 is not supported, although Model 7 and Model 8 show a significant main effect: Increases in the amount of time a person spends interacting with others is related to increases in the number of scripts he or she has. Again, network constraint (Hypothesis 5) is not significant. Hypothesis 6s is strongly supported – in all models, managerial position is significant and positive in predicting the number of scripts. The similarity of the results for predicting number of scripts and number of schemas is not surprising, given how correlated they are to each other. Among personality variables, only openness was included in the final models as a control. Surprisingly, openness is negative and significant in most of the models, indicating that those who are more open to new experiences (not conventional) actually make fewer distinctions between the kinds of activities they engage in with their social partners.

A slightly different set of results emerges when predicting the generality of scripts, however. Table 6 reports the results of Tobit regression on generality of scripts, which can only vary from 0 to 100. First, the control male is significant in all models; men in this dataset have higher generality of scripts, meaning they think they do more similar things with each of their relational partners. Second, personality has a more consistent effect on this dependent variable – agreeableness is significant in all models, indicating that those who are more pleasant (non-critical people) tend to think they do more similar things with others. The number of scripts is included as a control variable here, since the number of scripts (observations) in the dataset for each person influences the calculation of Cronbach's Alpha. This is because of the nature of the data: most often, the scripts that interviewees mentioned are ones that apply to only a few or fewer alters. Thus, each script added actually increases the Cronbach's alpha, because it makes all the relational partners who are NOT associated with the script look more similar (higher inter-correlation). Therefore, the number of scripts mentioned is controlled for here.

Hypothesis 1 (degree), Hypothesis 3 (interaction time), Hypothesis 5 (constraint), and Hypotheses 6a & 6b (manager) find no support in these models. The two hypotheses that are supported in predicting generality of scripts are Hypothesis 2 (daily interaction partners) and Hypothesis 4 (tenure). When one has a low level of interaction partners, increases in the number of interaction partners decreases the generality of scripts (which means it increases the variety of relational schemas). At higher levels, increases in the number of interaction partners increases the generality of scripts (meaning decreasing variety of schemas). Similarly, when tenure increases from a lower level, it decreases the generality of scripts (increasing variety of relational schemas); at higher levels of tenure, increases in tenure increase the generality of scripts (decreasing variety of schemas).

Hypothesis 7 states that variety of relational schemas increases relational acumen. To test this hypothesis, the three forms of variety of relational schemas, as well as control variables, were regressed on relational acumen. Tobit regression is used here, since relational acumen can only vary from -1 to 1. In these regressions, log likelihoods calculated were positive, making pseudo R-squared values meaningless. Therefore the goodness of fit measure reported for each model is the Chi-squared statistic for the likelihood ratio test comparing the model to one without predictors. Table 7 shows the results. While the number of schemas and scripts were not significantly associated with relational acumen, Model 5 shows that the generality of scripts is. The greater the generality of scripts (lower variety of relational schemas), the lower a person's relational acumen – in other words, the worse the person was at assessing the strength of his or her relationships.

Table 8 summarizes the various findings for each hypothesis across all three forms of variety of relational schemas.

TABLE 3: DESCRIPTIVE STATISTICS AND CORRELATIONS FOR VARIABLES

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Number of Schemas (DV)	17.63	7.42	5	30													
2. Number of Scripts (DV)	30.96	12.41	7	60	0.89												
3. Generality of Scripts (x100) (DV)	94.32	3.64	80.16	99.12	0.03	0.12											
4. Relational Acumen (DV)	0.35	0.21	-0.05	0.69	0.16	0.15	-0.46										
5. Contact Network Degree	21.67	7.24	0	28	0.33	0.25	-0.12	0.30									
6. Daily Interaction Partners	17.33	2.64	11.93	21.87	0.33	0.27	0.17	0.09	0.35								
7. Daily Interaction Hours	2.05	0.91	0.57	4.34	0.33	0.39	0.22	0.01	0.09	0.58							
8. Tenure	16.31	7.45	0.83	30.83	-0.16	-0.12	0.17	-0.27	-0.05	0.08	0.11						
9. Contact Network Constraint	0.18	0.16	0.13	1	-0.29	-0.29	0.12	-0.35	-0.79	-0.29	0.06	0.03					
10. Male	0.57	0.50	0	1	-0.09	-0.29	0.20	-0.20	0.12	0.05	-0.11	0.22	0.10				
11. Openness	5.27	1.19	1	7	-0.14	-0.20	-0.20	-0.09	-0.15	0.24	0.26	0.25	0.09	0.20			
12. Agreeableness	5.11	1.22	2.5	7	-0.14	0.00	0.36	-0.04	-0.30	-0.03	-0.20	-0.05	0.19	-0.22	-0.12		
13. Conscientiousness	6.10	0.92	4	7	-0.10	-0.05	-0.16	0.22	-0.09	-0.20	-0.07	0.09	-0.05	-0.09	-0.11	0.26	
14. Extraversion	4.73	1.67	1.5	7	0.01	-0.04	0.15	0.04	0.52	0.21	0.18	0.14	-0.31	0.06	0.38	-0.24	-0.24

TABLE 4: NEGATIVE BINOMIAL REGRESSION MODELS PREDICTING NUMBER OF SCHEMAS

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Male	-0.064	-0.127	-0.272	-0.254+	-0.103	-0.031	-0.087	-0.141	-0.120	-0.191	-0.257	-0.290+
	(0.211)	(0.198)	(0.175)	(0.154)	(0.172)	(0.165)	(0.189)	(0.187)	(0.198)	(0.142)	(0.176)	(0.174)
Openness	-0.039	-0.074	-0.245**	-0.214**	-0.135+	-0.207**	-0.080	-0.130	-0.064	-0.185**	-0.249**	-0.216*
	(0.082)	(0.078)	(0.090)	(0.080)	(0.069)	(0.076)	(0.072)	(0.080)	(0.079)	(0.062)	(0.088)	(0.090)
Agreeableness	-0.055	-0.074	-0.098	-0.106+	-0.067	-0.057	-0.052	-0.050	-0.074	-0.117*	-0.100	-0.083
	(0.075)	(0.070)	(0.066)	(0.058)	(0.061)	(0.057)	(0.067)	(0.065)	(0.069)	(0.051)	(0.062)	(0.062)
Manager		0.384+	0.487*	0.597**	0.337+	0.324+	0.262	0.349	0.378+	0.360*	0.500**	0.433*
		(0.211)	(0.207)	(0.188)	(0.181)	(0.167)	(0.212)	(0.215)	(0.210)	(0.147)	(0.191)	(0.195)
Contact Network Degree			0.008	0.112*								
			(0.014)	(0.049)								
Contact Network Degree (squared)				-0.004*								
				(0.002)								
Daily Interaction Partners					0.096**	0.854*						
					(0.035)	(0.431)						
Daily Interaction Partners (squared)						-0.022*						
						(0.012)						
Daily Interaction Hours							0.175*	0.779+				
							(0.106)	(0.478)				
Daily Interaction Hours (squared)								-0.123+				
								(0.095)				
Tenure									-0.008	0.159***		
									(0.012)	(0.038)		
Tenure (squared)										-0.005***		
										(0.001)		
Contact Network Constraint											-0.350	-6.123
											(0.492)	(4.957)
Contact Network Constraint (squared)												5.063
												(4.321)
Constant	3.396***	3.620***	4.542***	3.977***	2.160**	-3.966	3.147***	2.750***	3.701***	3.350***	4.803***	5.336***
	(0.545)	(0.519)	(0.801)	(0.764)	(0.681)	(3.541)	(0.559)	(0.619)	(0.533)	(0.383)	(0.564)	(0.729)
Observations	23	23	19	19	23	23	23	23	23	23	19	19
Pseudo-R^2	0.006	0.026	0.092	0.127	0.069	0.087	0.042	0.052	0.029	0.115	0.094	0.105

Standard errors are in parentheses. One-tailed tests for hypothesized variables except Manager; two-tailed tests otherwise.
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

TABLE 5: NEGATIVE BINOMIAL REGRESSION MODELS PREDICTING NUMBER OF SCRIPTS

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Male	-0.166	-0.225	-0.296*	-0.274*	-0.208	-0.172	-0.209	-0.256+	-0.222	-0.243*	-0.269+	-0.283+
	(0.179)	(0.152)	(0.146)	(0.132)	(0.131)	(0.127)	(0.138)	(0.139)	(0.152)	(0.123)	(0.144)	(0.152)
Openness	-0.037	-0.085	-0.215*	-0.191*	-0.139*	-0.186**	-0.091	-0.130*	-0.081	-0.168**	-0.217**	-0.209*
	(0.074)	(0.064)	(0.085)	(0.078)	(0.057)	(0.064)	(0.056)	(0.063)	(0.066)	(0.058)	(0.082)	(0.086)
Manager		0.499**	0.571**	0.682***	0.461**	0.453**	0.377*	0.446**	0.497**	0.465***	0.570***	0.558**
		(0.174)	(0.185)	(0.176)	(0.148)	(0.140)	(0.164)	(0.169)	(0.174)	(0.138)	(0.172)	(0.176)
Contact Network Degree			0.007	0.100*								
			(0.012)	(0.045)								
Contact Network Degree (squared)				-0.003*								
				(0.002)								
Daily Interaction Partners					0.082**	0.587+						
					(0.028)	(0.366)						
Daily Interaction Partners (squared)						-0.015+						
						(0.011)						
Daily Interaction Hours							0.189*	0.648*				
							(0.082)	(0.380)				
Daily Interaction Hours (squared)								-0.093				
								(0.075)				
Tenure									-0.003	0.113***		
									(0.010)	(0.035)		
Tenure (squared)										-0.003***		
										(0.001)		
Contact Network Constraint											-0.490	-1.553
											(0.417)	(3.771)
Contact Network Constraint (squared)												0.942
												(3.322)
Constant	3.731***	3.893***	4.458***	3.944***	2.685***	-1.345	3.505***	3.220***	3.923***	3.542***	4.706***	4.813***
	(0.371)	(0.319)	(0.555)	(0.555)	(0.485)	(2.952)	(0.318)	(0.382)	(0.333)	(0.271)	(0.429)	(0.571)
Observations	23	23	19	19	23	23	23	23	23	23	19	19
Pseudo-R^2	0.009	0.049	0.091	0.118	0.089	0.099	0.075	0.084	0.049	0.098	0.097	0.098

Standard errors are in parentheses. One-tailed tests for hypothesized variables except Manager; two-tailed tests otherwise.
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

TABLE 6: TOBIT REGRESSION MODELS PREDICTING GENERALITY OF SCRIPTS

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Male	3.109*	4.230*	4.717*	5.463*	4.161*	4.247**	4.057*	4.515**	4.028*	5.762**	4.636*	4.673*
	(1.403)	(1.499)	(1.883)	(1.864)	(1.518)	(1.424)	(1.485)	(1.527)	(1.492)	(1.478)	(1.902)	(1.962)
Agreeableness	1.434*	1.634**	1.732*	1.975**	1.631**	1.629**	1.675**	1.697**	1.632**	2.094***	1.657*	1.648*
	(0.528)	(0.515)	(0.638)	(0.630)	(0.515)	(0.483)	(0.508)	(0.498)	(0.507)	(0.482)	(0.601)	(0.614)
Number of Scripts	0.078	0.132*	0.135+	0.196*	0.126+	0.124+	0.105	0.098	0.133*	0.202**	0.136+	0.137+
	(0.054)	(0.061)	(0.070)	(0.079)	(0.065)	(0.061)	(0.067)	(0.066)	(0.060)	(0.059)	(0.071)	(0.072)
Manager		-2.917	-3.022	-5.330+	-2.918	-2.627	-3.104+	-3.348+	-2.830	-3.337*	-2.847	-2.838
		(1.802)	(2.289)	(2.710)	(1.799)	(1.695)	(1.782)	(1.764)	(1.776)	(1.577)	(2.211)	(2.213)
Contact Network Degree			0.029	-0.719								
			(0.117)	(0.536)								
Contact Network Degree (squared)				0.027+								
				(0.019)								
Daily Interaction Partners					0.076	-5.259*						
					(0.276)	(3.016)						
Daily Interaction Partners (squared)						0.157*						
						(0.089)						
Daily Interaction Hours							0.808	-2.137				
							(0.886)	(3.118)				
Daily Interaction Hours (squared)								0.632				
								(0.643)				
Tenure									0.067	-0.745*		
									(0.076)	(0.322)		
Tenure (squared)										0.023**		
										(0.009)		
Contact Network Constraint											0.102	2.85
											(4.026)	(36.278)
Contact Network Constraint (squared)												-2.407
												(31.586)
Constant	82.764***	80.061***	78.295***	77.499***	78.952***	123.079***	79.025***	81.937***	79.007***	79.344***	79.255***	78.879***
	(3.764)	(3.938)	(6.056)	(5.782)	(5.639)	(25.408)	(4.032)	(4.936)	(4.055)	(3.576)	(4.662)	(6.790)
Observations	23	23	19	19	23	23	23	23	23	23	19	19
Pseudo-R^2	0.067	0.086	0.081	0.099	0.087	0.111	0.093	0.101	0.093	0.139	0.08	0.08

Standard errors are in parentheses. One-tailed tests for hypothesized variables except Manager; two-tailed tests otherwise.
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

TABLE 7: TOBIT REGRESSION MODELS PREDICTING RELATIONAL ACUMEN

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Male	-0.054				
	(0.069)				
Manager	0.116	0.109	0.058	0.059	0.080
	(0.084)	(0.085)	(0.097)	(0.103)	(0.084)
Conscientiousness	0.053	0.056	0.086+	0.085+	0.069
	(0.037)	(0.037)	(0.047)	(0.046)	(0.042)
Tenure	-0.007	-0.008+	-0.009+	-0.009+	-0.008+
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Number of Schemas			0.002		
			(0.006)		
Number of Scripts				0.001	
				(0.003)	
Generality of Scripts (x100)					-0.022*
					(0.010)
Constant	0.160	0.124	-0.079	-0.051	2.067*
	(0.238)	(0.236)	(0.330)	(0.328)	(0.987)
Observations	31	31	23	23	23
Chi-squared	6.896	6.285	7.355	7.251	11.596
Prob > Chi-squared	0.1415	0.0985	0.1183	0.1232	0.0206

Standard errors are in parentheses. One-tailed tests for hypothesized variables; two-tailed tests otherwise.
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

TABLE 8: SUMMARY OF HYPOTHESES, VARIABLES, PREDICTED SIGNS OF COEFFICIENTS, AND RESULTS

Hypothesis	Dependent Variable	Independent Variable	Predicted Sign	Supported Results
H1: Number of Contacts has a curvilinear effect on Variety of Relational Schemas	Number of Schemas	Degree	+	Support
		Degree (squared)	-	Support
	Number of Scripts	Degree	+	Support
		Degree (squared)	-	Support
	Generality of Scripts	Degree	-	
		Degree (squared)	+	
H2: Average Daily Interaction Partners has a curvilinear effect on Variety of Relational Schemas	Number of Schemas	Daily Partners	+	Support
		Daily Partners (squared)	-	Support
	Number of Scripts	Daily Partners	+	Marginal Support
		Daily Partners (squared)	-	Marginal Support
	Generality of Scripts	Daily Partners	-	Support
		Daily Partners (squared)	+	Support
H3: Average Daily Interaction Hours has a curvilinear effect on Variety of Relational Schemas	Number of Schemas	Interaction Hours	+	Marginal Support
		Interaction Hours (squared)	-	Marginal Support
	Number of Scripts	Interaction Hours	+	
		Interaction Hours (squared)	-	
	Generality of Scripts	Interaction Hours	-	
		Interaction Hours (squared)	+	
H4: Tenure has a curvilinear effect on Variety of Relational Schemas	Number of Schemas	Tenure	+	Support
		Tenure (squared)	-	Support
	Number of Scripts	Tenure	+	Support
		Tenure (squared)	-	Support
	Generality of Scripts	Tenure	-	Support
		Tenure (squared)	+	Support
H5: Structural Holes has a curvilinear effect on Variety of Relational Schemas	Number of Schemas	Constraint	+	
		Constraint (squared)	-	
	Number of Scripts	Constraint	+	
		Constraint (squared)	-	
	Generality of Scripts	Constraint	-	
		Constraint (squared)	+	
H6a: Management Position has a positive effect on Variety of Relational Schemas	Number of Schemas	Manager	+	Support
	Number of Scripts	Manager	+	Support
	Generality of Scripts	Manager	-	
H6b: Management Position has a negative effect on Variety of Relational Schemas	Number of Schemas	Manager	-	
	Number of Scripts	Manager	-	
	Generality of Scripts	Manager	+	
H7: Variety of Relational Schemas has a positive effect on Relational Acumen	Relational Acumen	Number of Schemas	+	
		Number of Scripts	+	
		Generality of Scripts	-	Support

Discussion

The goal of this study is to test the idea that there is a tension between the adaptive benefit of having a greater variety of relational schemas and the cognitive costs of holding those schemas in memory. Although we must exercise some caution in interpreting the findings due to the low number of observations, the study provides the opportunity for a rich exploration of the structural and behavioral determinants of relational schema development. By using a site with a small size, more detailed interviews on people's relationships with each other was possible, allowing the inductive coding of scripts and schemas. Moreover, this site was ideal for collecting the diverse sets of data required, including network survey data and interaction data.

One of the findings of this study is that a person's length of experience (tenure) in a social environment has a curvilinear effect on the variety of his or her relational schemas, across all three ways of characterizing the variety of relational schemas. As people with lower amounts of tenure in this setting increase in tenure, the number of schemas and the number of scripts they hold increase, while the generality of their scripts decreases. Here, increases in social experience lead to greater variety of cognitive models for social interaction, presumably because increases in social experience reflect exposure to a greater diversity of social situations over time. However, at higher levels of social experience, increases in tenure have the reverse effect. Instead, increases in tenure lead to greater cognitive lumping, as employees assimilate new experiences into pre-existing relational schemas rather than create new ones. The mechanism hypothesized here is cognitive overload; as relational schemas develop over time, they take up more space in the mind, making it less easy to respond quickly to social stimuli. As social experience progresses to higher levels, the mental cost of adding greater variety of relational schemas – in the form of new scripts and schemas, especially ones that are applied specifically to certain individuals – comes to outweigh the benefits of having relationship-specific schemas.

Further, a person's embeddedness in a social context, specifically the number of social contacts of a person and the average number of daily interaction partners, also has a curvilinear relationship with the number of schemas and the number of scripts a person develops. The key mechanism is the same as with tenure. To the extent that greater numbers of social ties and interaction partners indicate greater social exposure, increases in social exposure provide an opportunity to adapt to new social situations, but come at the cost of greater mental complexity.

An interesting result is the pattern of findings relating to structural holes and managerial position. It was hypothesized that both variables would influence variety of relational schemas through the mechanism of social information flow – both managers and people in structural holes would have greater access to information about others, leading them to develop greater variety of relational schemas.

However, the structural holes hypothesis was not supported. Even so, managers were found to have more schemas and scripts than subordinates. Perhaps managers have higher schemas and scripts not because they have greater access to information about others, but because their job requires them to be more attentive to their own social interactions with others. The mechanism here is unclear, and deserves further study. Interviews with managers indicate that managers do consciously pay attention to others' relationships, particularly the relationships of their subordinates. Yet if knowledge of others' relationships affects the development of relational schemas, then one would expect that structural holes should also affect relational schemas, because people in structural holes receive more information about others' relationships. Further research should make these mechanisms more clear. Also, further research should explore whether the nonsupport of the competing hypothesis about management position is due to corporate culture. Given the literature on power and attention to others, one would expect that managers would be less attentive to others, making them cognitively lump more of their relationships. Yet this was not the case at ManuCorp. One possible explanation is that in this department, managers felt less dominant and powerful, due to a more egalitarian and less formal environment.

Together, these findings support the idea of a tradeoff between the value of having more specific relational schemas and the cognitive overload of those schemas. To more fully demonstrate this tradeoff, one aspect of the value of having more specific schemas was tested. Having more specific relational schemas should allow a greater ability to attend to, process, and respond to social cues that different relational partners provide, and this should lead to a more accurate perception of each relationship. The finding that the generality of one's scripts decreases relational acumen shows support for this idea that increasing variety of relational schemas is adaptive. When people gain social experience – particularly over time – and increase the variety of their schemas, they gain a greater ability to understand their social environment. Thus, when the constraints of cognitive overload take effect and the tendency to cognitively "lump" relations increases, the cost is lower relational acumen. Paradoxically, high levels of social experience and social embeddedness provide not enhanced ability to navigate social interaction, but instead more cognitive lumping – seeing social situations and relationships as the same, preventing the person from seeing unique features of each new situation or relationship.

Conclusion

This paper makes contributions to two literatures. It contributes to the relational schemas literature in cognitive psychology, by showing how social experience in a particular context guides the development of schemas. While many studies of relational schemas describe the development of these schemas as experience-based (e.g. Safran 1990), how this experience is accumulated over time in adults is less clear. This is because the foundational work used to explain the development of relational schemas is attachment theory (Bowlby 1970), which primarily explains the formation of working models (relational schemas) in a child's early development, and primarily focuses on close or intimate relations. Even though attachment theory has been extended to adults (Hazan and Shaver 1987), it still focuses on romantic relations. This study contributes to this interpersonal cognition literature by demonstrating that increases in exposure to new social situations, even in adults and in the context of work, can lead to the development of new relational schemas and new scripts. Similarly, this study demonstrates concretely the effect of cognitive miserliness suggested in early research on relational schemas (Abelson 1981) but never explored empirically. While the existence of schemas themselves are evidence of cognitive miserliness – since schematic processing simplifies cognition – it has not been shown to what extent the amount of relational schema development (in the form of more specific schemas) could be affected by cognitive overload.

One avenue for future exploration is to distinguish between age and tenure, which is contextual. In the present study, employees' ages are unknown, but are likely correlated with their tenure in the organization. Thus, the results here may reflect the growth of schemas and then cognitive overload associated with increased social experience over the entire life course. On the other hand, it is possible that contextual activation of schemas allows a person to develop relational schemas in different contexts independently. For example, if relational schemas at work are work-specific, in the sense that they are activated in memory when at work and not activated when not at work, and relational schemas for other domains are similarly context specific, then the process of cognitive overload producing cognitive lumping will be context specific as well. In that case, the level of one's experience in any social context, such as tenure in a work organization, would independently influence the variety of relational schemas developed in that context.

This study also contributes to the literature on network perception accuracy, by showing how the variety of relational schemas we hold increases one form of network perception accuracy (relational acumen). This finding is consistent with other studies on schema-based network perception. Researchers have found that people perceive the social relationships around them schematically, for example by perceiving higher levels of reciprocated relationships (Krackhardt and Kilduff 1999) and by perceiving social networks as having loosely connected dense clusters of people ("small worlds") (Kilduff, Crossland, Tsai, and Krackhardt 2008). The present study not only corroborates that we schematize social information, but also suggests that how *much* we schematize such information varies from person to person, and is dependent on how much social exposure we have obtained.

Chapter IV: Information Flow in Interactions (Paper 2)

SUMMARY

This study proposes a new technique for analyzing time-ordered communication data, which is data on people's physical or virtual interactions with each other (emails, physical movement, messaging, etc). This type of data is becoming ever more available, and presents an opportunity to analyze the flow of information through chains of interactions. I develop measures to identify the rate and timeliness of information flow through a social group, and expect that they should be related to (but distinct from) current measures of social network centrality. To validate these measures, I employ them to understand the flow of information in a department of a manufacturing firm, using data from a nine week period where employees' physical movements were electronically tracked. I demonstrate how individuals' social network position relates to patterns of interactions, which leads to access to information – a causal relationship which is often assumed but not tested in social network research.

THEORY

A basic tenet of social network research is that relationships carry information. People who are in advantageous network positions have greater and faster access to the information that brings new ideas (Burt 2004), access to jobs (Granovetter 1974), and promotions (Burt 1992). A person's network ties also convey information about role expectations (Podolny and Baron 1997) and practices (such as a co-director's information about corporate strategies and structures (Haunschild and Beckman 1998)). Underpinning all of this research is the assumption that when a relationship exists, the two people will communicate with each other. A general distinction is often made between strong ties, which have frequent communication and are close, versus weak ties, which have infrequent communication and are more distant (Granovetter 1973). Yet, even when distinctions are made between weak and strong ties, most network literature treats relations as being concurrent: each of a person's ties are assumed to be active at each moment in time – in other words, communication is assumed to occur.

However, this is not how people use their networks in real life. Even in the digital age, we are each constrained by time, space, our limited ability to multitask, and the availability of others. As a result, we experience our networks sequentially (Gibson 2005). Meeting with a colleague or talking on the phone with a friend at one moment means not interacting with others until a later time. Changing physical location, such as taking a trip or moving to another city, means decreasing time spent with some contacts, at the same time as it might mean increasing time spent with others. As a result, although the overall quality and strength of the relation may be considered the same, the frequency of contact and communication varies highly both across relations and within a single relation over time.

While attempts to address this gap in the social network literature remain underdeveloped, two different approaches have been explored. First, there are direct attempts to measure the amount of communication across network relations. People are inaccurate at recalling the frequency of communication they have with all their alters (Marsden 1990), so direct observation or archival data is required to get measures of communication patterns. Archival email data, cell phone data, and electronic movement tracking devices provide such objective information, and they are increasingly used to assess the existence of relations and extent of communication between individuals (e.g. (Waber, Aral, Olguin Olguin, Wu, Brynjolfsson, and Pentland 2011; Wu, Waber, Aral, Brynjolfsson, and Pentland 2008)). Using email data, Aral and Van Alstyne (2011) found that the frequency of communication (what they call "bandwith") is crucial to understanding a person's access to novel information through network ties. They show that an important idea in the social network canon, that "weak" ties provide novel information (Granovetter 1973), must be understood differently: weak ties provide potential access to novel information, but the actual novel information received depends on a) how frequently people communicate to transfer that information and b) aspects of the environment such as how quickly information is generated. In some environments, it is relations with high communication frequency ("strong ties") which actually provide the most novel information. Aral and Van Alstyne's findings highlight that the choices people make about when and how often to communicate – how they enact their relations – can fundamentally alter the network benefits they receive.

However, although the approach of measuring communication frequency has provided new insights, it still does not fully take into account the *sequences* of action that occur in the course of real social interaction. A second approach, which exists in the diffusion literature, has begun to face this challenge directly. Here, the emphasis is on understanding the effect temporal ordering has on diffusion. Morris and Kretzschmar (1995; 1997) studied the effect of concurrent versus sequential sexual relationships on the diffusion of sexually transmitted diseases, finding that when people have concurrent relations, diseases spread much faster. Extending this insight, Moody (2002) developed a method for identifying diffusion paths through a network where the time-ordering of relationships is taken into account. To take an example, suppose A has a relationship with

B, and after that relationship is dissolved, B has a relationship with C. Moody's method would identify A → C as a possible diffusion path, because A could infect B, and B could then infect C. However, C could not infect A, unless B's relationship with A and C were instead concurrent. In identifying the effect of time-ordering on diffusion, Moody's analysis shows that the timing of relationships can have dramatic effects on diffusion; the timing and sequencing of relationships operates like a "railroad switch" which channels information or resources.

Extending this line of inquiry in diffusion further, Gibson (2005) has argued that even when relationships *are* concurrent, the day-to-day timing of contact between relational partners also acts as a railroad switch which constrains how information, goods, and infection may spread. Gibson uses a simulation model to illustrate that scheduling constraints (such as being able to meet with only one alter at a time) significantly affect diffusion: While we might assume that highly connected actors are "super-spreaders", schedule constraints can actually make such actors bottlenecks, preventing diffusion until they can manage to meet with enough of their alters.

This line of research in diffusion brings focus to the very real constraints of time and sequencing on interpersonal interaction. However, the studies mentioned focus on diffusion as a process where a particular disease, practice, or piece of information spreads through a network: an actor is or is not infected, and once infected, remains infected. This approach has not yet been extended to analyze the ongoing production and dissemination of information through a social network. We do not yet know how to measure an actor's ongoing (and changing) susceptibility to information arising from repeated – but time-ordered – communication events.

Returning to the original problem identified at the outset, much of the current research in social networks focuses on the flow of information between actors, but assumes that relationships evenly and concurrently convey this information. To summarize, two lines of inquiry have recently shown that relaxing this assumption causes significant changes in our understanding of network processes. Research on email communication has highlighted that the frequency of communication matters such that strong relations with very frequent communication can channel more novel information than weak relations with very infrequent communication. And research on relationship timing and scheduling has shown that the order of contact can stop information flow in its tracks or push it along at higher speeds through a network.

In this paper I extend insights from both lines of research to develop a method for analyzing information flow given time-ordered repeated communication events within a network. Unlike Gibson and Moody, I am not interested in an actor's susceptibility to infection, but rather the actor's ongoing acquisition of information from all others in the network. By measuring the actual pattern of interaction between actors, I incorporate the insight that communication – which provides the opportunity for information sharing – can vary both across and within ties over time. However, I place each interaction in context, existing within a chain of previous and subsequent interactions, where an actor may carry knowledge from one interaction to another. This realized pattern of interaction between people shows how people live their networks, within the constraints of time, space, and formal and informal scheduling processes.

In the next section, I describe the mechanics of this proposed method, and show how it can be used to generate useful measures of information flow for each actor in a network. To validate these measures, I study the movement patterns and social networks of a department of ManuCorp. The measures of information flow should be related to, but distinct from, measures of network centrality, in predictable ways. Finally, I discuss the generalizability of these measures for broader datasets involving discrete time-ordered communication events.

INFERRING INFORMATION FLOW FROM TIME-ORDERED BEHAVIORAL DATA

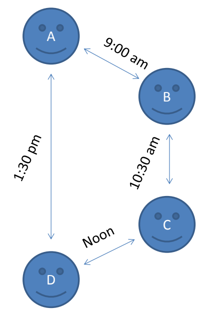
The goal of this method is to measure each person's ongoing access to information that is generated all the time, by everyone. Rather than trace the diffusion of specific pieces of information or ideas, this approach traces the potential flow of a multitude of information from a multitude of sources. With each interaction, new information is generated that the parties can acquire from each other. Because of this, the method is content neutral. As in real life, the information that can flow from person to person may be an idea, an opinion, how a person is feeling at that moment, a piece of news, a piece of gossip, or a report about an event, among other things. Any of these items might give a person a social advantage, though the value of a particular item of information is uncertain – it may be useless or highly valuable. Thus, advantage comes to those who can receive more information from a broader set of sources, and receive it sooner than others (Burt 1992).

For this reason, the focus of the analysis will be to identify the breath of actors' *access* to flows of information and the *timeliness* of the information received. As Moody's (2002) analysis indicates, the ordering/sequencing of relations affects who can have access to what information. In addition, I argue that the ordering of interactions affects timeliness. If each day, Person A talks to Person B before talking to Person C, then Person C's information about Person B is fresher than Person B's information about Person C. Even though both B and C are equally tied to A – they both obtain information about each other by interacting with Person A once a day – the timeliness of the information they can receive differs. As a result, the method records not just who can receive information from whom, but when.

Without knowing the content of the information discussed in each interaction, this method cannot identify precisely what information each person has gained through his or her interactions. Instead, the focus here in on what a person's pattern of interactions *could* provide, and represents the maximum possible transmission of information from person to person. In other words, a person's calculated access to and timeliness of information represents *potential* amounts, rather than expected amounts. The current model is relatively simplistic, since it takes information transmission as instantaneous: when an interaction occurs, transmission of each person's knowledge, which includes each person's prior knowledge gained from earlier interactions, is instantaneous. This can be relaxed in the future, for example via limitations on transmission and/or knowledge decay over time. The model also ignores other ways of gaining information, for example through broadcasts of information that are outside of interactions or by direct observation. However, those other forms of information acquisition are ignored by social network analysis as well.

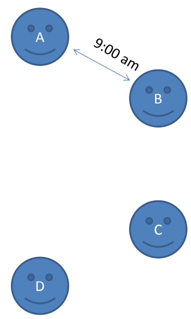
To illustrate the method, a small example will be used. In this example (Figure 2), Persons A, B, C, and D have a sequence of four interactions in a day. Please consult the figures below. In Figure 3-Figure 5, a matrix records the current state of possible knowledge of each of the people, at three different time points in the day, given how information could flow through their interactions. With each new interaction, two things happen: the two people involved can exchange new information directly with each other, and they also can convey to each other information they acquired from previous interactions. Of course, not all information is conveyed in each interaction; rather, each interaction provides the opportunity to convey information. Each row in the matrix records the maximum possible information a person could hold from[9] each of the other people (columns), with the date of the information noted.

FIGURE 2: EXAMPLE



- Each interaction provides the opportunity to convey information learned in prior interactions
- But information carried from prior interactions is old.

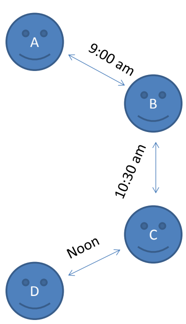
FIGURE 3: EXAMPLE AT 9:00AM



The distribution of knowledge:

	A	B	C	D
A knows:		Info @ 9:00 am		
B knows:	Info @ 9:00 am			
C knows:				
D knows:				

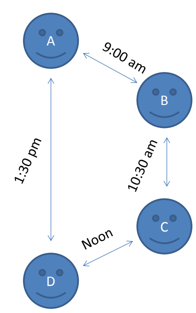
FIGURE 4: EXAMPLE AT NOON



The distribution of knowledge:

	A	B	C	D
A knows:		Info @ 9:00 am		
B knows:	Info @ 9:00 am		Info @ 10:30 am	
C knows:	Info @ 9:00 am	Info @ 10:30 am		Info @ Noon
D knows:	Info @ 9:00 am	Info @ 10:30 am	Info @ Noon	

FIGURE 5: EXAMPLE AT 1:30PM



The distribution of knowledge:

	A	B	C	D
A knows:		**Info @ 10:30 am**	Info @ Noon	Info @ 1:30 pm
B knows:	Info @ 9:00 am		Info @ 10:30 am	
C knows:	Info @ 9:00 am	Info @ 10:30 am		Info @ Noon
D knows:	**Info @ 1:30 pm**	Info @ 10:30 am	Info @ Noon	

Starting with Figure 3, it is 9am when A and B interact. Since this is the beginning of the example, no one yet knows anything from anyone else, except that A and B get to learn whatever is new with each other. Thus, in the knowledge matrix, A can receive information from B that is current – and therefore dated 9am, and B can receive information from A that is dated 9am. In Figure 4, two more events have occurred: B and C interacted at 10:30am, and C and D interacted at noon. When B and C interacted at 10:30am, B could learn

[9] This information should be understood as anything that person might have communicated at that moment in time. For instance, an opinion, a fact, an idea, etc. This is information that originates with this person, rather than something that the person is passing along from others. (Because information passed along from others is recorded in the matrix in the column of the person from whom it originated.) I speak of this information as being whatever "is new" with that person, as of the time of that interaction. The person's interactant can later pass on that information to others, though it is still dated as of the time of the earlier interaction.

whatever was new with C at that moment, and C could learn whatever was new with B at that moment. This is noted in the knowledge matrix with information dated 10:30am in cells (row B, column C) and (row C, column B). In addition, however, C had the opportunity to learn the old information B was carrying from A. As a result, C's knowledge now includes information from A as of 9am, in cell (row C, column A). Similarly, when C and D interact, they each can learn whatever was new with each other at noon, and D can learn the information that C was carrying from both B and A. Figure 4 reflects the state of affairs at noon. At this point, C and D can know something from everyone, although some of their information is a bit old.

At 1:30pm, shown in Figure 5, something new happens. D and A interact, and through this A can learn what is new with D. However, D already knew something from A (dated 9am) before the interaction; by interacting with A, D's information from A gets <u>updated</u> to the current time. Also during this interaction, A can learn information through D about C (from whom A did not have any information) and B (from whom A only had information as of 9am). A's information about B gets updated to what was new with B at 10:30am, because that is the information D was carrying.

After this last interaction, note that although each of the people had an equal number of interaction partners (two), their resulting information could not be the same. Person B has the least information, and it is the oldest. And notably, Persons A and D each have received updated information from one other person. That is, during the course of the day, A and D could receive two pieces of information from one of the others, indicating that their flow of information is higher.

Expanding from this small example to a real dataset with tens or hundreds of interactants over a long period of time is simple analytically, though it requires significant computational resources. The time-ordered interactions must be processed sequentially, using an algorithm which identifies the effect of that interaction on the knowledge matrix – an NxN matrix, where N is the number of individuals. See Appendix 2 for the algorithm. The goal is to record each time a person can receive new information from another person.

To use these data to calculate access to information and the timeliness of information, examine Person A. See Figure 6, which shows each time A receives new information originating from others. A's access to information from each other person can be measured as the frequency with which A can receive information originating from that person during the whole time period. This is the <u>updating frequency</u> for A with respect to that other person. It can be thought of as assessing how well informed A is about that person. For example, A's knowledge about B comes from two different moments in time: At 9am, A interacted with B, having the opportunity to find out what was new with B at that point, and then at 1:30pm, A interacted with D, having the opportunity to find out information that was new with B as of 10:30 (as transmitted to C and subsequently to D). As a result, A's updating frequency with respect to B is 2. By contrast, A's updating frequency with respect to D is 1. A was more informed about B (meaning A could receive more information originating from B) than D – even though A interacted with each only once in the day.

The timeliness of A's information can be calculated based on how long it took A to receive each piece of information during the time period. When A interacts directly with another person, the information A receives is current; but when A receives information from one person originating from another person, that information is old. The <u>age of</u>

information[10] is the average time it takes for A to receive information from each of the others. It indicates how timely A is informed about that person. For instance, the age of information A received from D is 0, but the age of information A received from B is 1.5 hours. So, while A learns more about B than D, the information A receives from B is less timely than the information from D.

FIGURE 6: A'S KNOWLEDGE IN THE EXAMPLE

A's Knowledge	
About B:	
At 9:00 am, learned B's 9:00 am info At 1:30 pm, learned B's 10:30 am info	Frequency of Info = 2 Age of Info = (0 hrs+3 hrs)/2 = 1.5 hours old
About C:	
At 1:30 pm, learned C's Noon info	Frequency of Info = 1 Age of Info = 1.5 hours old
About D:	
At 1:30 pm, learned D's 1:30 pm info	Frequency of Info = 1 Age of Info = 0 hours old

While these two measures, updating frequency and age of information, are dyadic, they also aggregate to produce meaningful descriptions of a person's overall access to and timeliness of information. The following measures (Table 9) summarize how a person receives information through interactions with others. Collectively, I refer to these as measures of information flow.

[10] I use the word "age" here ignoring the actual content of the information. It could be that the information is "old" in the sense of referring to events a long time ago, such as when a person talks about something she learned in a prior job. However what matters for this analysis is only the length of time this information takes to traverse the network via communication events. Thus, I only use "age" to refer to time in transmission. It does not refer to the original generation of the content of the information.

TABLE 9: INFORMATION FLOW MEASURES

Individual Level Measures of Access to Information	
Average Updating Frequency	Calculated as the average updating frequency a person has across all others in the network, over the time period studied. This measures how often a person can learn about all others in the group, and represents how well A is informed in general.
Standard Deviation of Updating Frequency	Calculated as the standard deviation of the updating frequencies a person has across all others in the network, over the time period studied. This measures the degree to which information received is from a few or many others in the group, and represents how broad or cliquish A's information about others is.
Individual Level Measures of Timeliness of Information	
Average Age of Information	Calculated as the average age of information a person has across all others in the network, over the time period studied. This measures how long it took information about all others in the group to reach A, and represents how timely A is informed in general.
Standard Deviation of Age of Information	Calculated as the standard deviation of the ages of information a person has across all others in the network, over the time period studied. This represents how even or skewed the timeliness of A's information about others is.

Comparing Information Flow and Network Centrality Measures

Because these new measures are indicators of constructs that social network analysis also attempts to measure, they should be related.

Access to Information: The network centrality measures Degree and Closeness are often used to measure a person's access to information in a network. A person with high Degree has more relational partners to interact with, which should bring that person a higher volume of information from others. Similarly, a person with high Closeness is "closer" (fewer number of links) to a wider number of people, and so their interactions should bring more information from others overall. As I have argued above, the average updating frequency of a person should also reflect this access to information. Thus, I expect that both social network Degree and Closeness should be related to Average Updating Frequency.

However, conceptually, these measures are quite different. Social network data gathered via surveys ("who do you know", "who do you seek advice from", "who are your friends") represent people's *potential* sources of information. Who one *actually* interacts with on a day-to-day basis, while based on one's social network, is a matter of personal choice, situational factors, and serendipity. Since the information flow measures are based on these actual interactions, they reflect not just enduring relations, but also the constraints of time and space, organizational constraints, and chance. As a result, the information flow measure Average Updating Frequency should be distinct from the social network measures of Degree and Closeness.

In addition, there is no current social network analogue to the Standard Deviation of Updating Frequency, which represents how broad (or cliquish) a person's information sources are. This is because for social network analysis, when a person is connected in a network, it is assumed that information flows evenly from that person along all paths to all others in that component of the network.[11] However, actual behavioral patterns can create rifts within a component of a network, when people know each other but interact much less frequently. The Standard Deviation of Updating Frequency will capture the effects of these rifts as well as other sources of variation in information flow which are the result of variation in interaction frequency and ordering.

Timeliness of Information: The network centrality measure Betweenness is used to measure a person's timeliness of information in a network. A person with high Betweenness (meaning a person on a greater numbers of shortest paths) is more likely to receive

[11] A component is a group of connected actors.

information sooner than others. In addition, the network measure Constraint has also been understood as reflecting the timeliness of a person's information (Burt 1992). A person who has relationships with people who themselves are already connected – or who have relationships to the same other third parties – has a constrained network. Constraint is often used to measure the novelty or diversity of information a person has access to, however it can also reflect how quickly information is received compared to others. The Average Age of Information of a person should also reflect this timeliness. Thus, I expect that the social network measures Betweenness and Constraint should be related to the information flow measure Average Age of Information. However, as mentioned above, conceptually these variables are different. I expect that Average Age of Information will be related but distinct from Betweenness and Constraint, since the Average Age of Information reflects the sequence of realized day-to-day communication, rather than time-invariant enduring relationships.

As with the Standard Deviation of Updating Frequency, there is not a current social network analogue to the Standard Deviation of Age of Information, which represents the skew in the timeliness of information from others.

METHODS

Data

This study uses social network and demographic data from ManuCorp at Time 1 (n=33) and interaction data from Time 2 (n=34); in total, complete data is available for 28 employees. At Time 2, time-ordered face-to-face interactions were calculated for a period of nine weeks. All movements recorded were on a single floor, which comprised all of the department's offices. Using this data, interactions between people are assumed to occur when those people are within five feet of each other for more than thirty seconds.

While this dataset provides a small number of available observations (the level of analysis is the employee), it is valuable in providing such comprehensive data. The focus of analysis here is to provide evidence that the interaction measures are meaningfully related to, but different from, established network measures, in order to spur future research using interaction measures.

Measures

Information flow measures: See the Appendix for the algorithm which calculates updating frequency and age of information from time-ordered interaction data. After processing all of the interactions at Time 2, the Updating Frequency (directional dyadic measure) for each person A with respect to each other person B is calculated as the number of rows in the update log where Person 1 = A and Person 2 = B. As noted earlier, the individual level Average Updating Frequency and Standard Deviation of Updating Frequency is calculated as the average and standard deviation of the dyadic Updating Frequencies. The Age of Information (directional dyadic measure) for each person A with respect to each other person B is calculated as the average of (Information Time – Interaction Time) over all rows in the update log where Person 1 = A and Person 2 = B. The individual level Average Age of Information and Standard Deviation of Age of Information are calculated based on those dyadic results.

Interaction Time: How much time (in hours) each person spends interacting per day on average during the movement tracking at Time 2.

Daily Interaction Partners: This variable reflects how many others a person typically interacts with during the movement tracking at Time 2. It is the average number of interaction partners per day, regardless of whether those interaction partners are the same day-to-day or different sets of people each day.

Social Network Degree: Degree centrality is the number of relationships one has in a social network. This is calculated separately for the contact network and the advice network. In the social network survey at Time 1, each person was presented with a roster of the department and asked to indicate which people he or she does not know ("whom you interact with as a mere 'hello' or less"), with the remaining people being people he or she does know. A relationship in this network exists when both people report that they have a relationship (they both do know each other more than a mere "hello"). In the same social network survey, each person was also asked to indicate those people to whom he or she either went for advice or gave advice. The advice network is a directional network: An outgoing advice tie exists when both people confirm that the person seeks advice from the other person, and an incoming advice tie exists when both people confirm that the person has given advice to the other person. Degree in the advice network is "in" degree – the number of incoming ties, reflecting how many other people seek advice from the focal person.[12]

Social Network Closeness: Closeness centrality is the inverse of a person's average distance to all other nodes (where the distance to other nodes is the shortest number of links that must be crossed to get to the other node), calculated separately for the contact network and the advice network.

[12] All analysis was also performed with out-degree, and the results are substantively the same as in-degree.

Social Network Betweenness: Betweenness centrality is based on the number of shortest paths on which the focal person is located. It assesses how well positioned a person is to capture and control information flows (Freeman 1977). Betweenness scores are standardized, and are calculated separately for the contact network and advice network.

Social Network Constraint: The concept of constraint (Burt 2002) assesses how redundant the person's contacts are, in the sense of providing access to the same third parties. A low level of constraint indicates that the person's network is high in structural holes – it provides greater access to diverse and more timely information. Calculated for both the contact and advice networks.

Sex: Men and women may differ in how much they interact with others and how many of their social contacts they interact with regularly. This variable is coded 1 for men and 0 for women, and is labeled "Male" for ease of interpretation.

Management position: Managers may spend more time interacting and may interact with more people due to the coordinator roles of their position. This variable is coded 1 for supervisors and 0 for non-supervisors.

RESULTS

Figure 7-Figure 10 show the distributions of Average Update Frequency, Standard Deviation of Update Frequency, Average Age of New Info, and Standard Deviation of Age of New Info, and Table 10 displays descriptive statistics and correlations for these and other variables. Average updating frequency ranges from 64 to 311, and is interpreted as the average number of times each person had the potential to receive information from each of their colleagues (directly or indirectly) during the course of the nine weeks, given their interaction patterns. Translated to a weekly basis, this means that some people came into

contact (directly or indirectly) with their colleagues as little as 7 times per week per colleague; others came into contact with their colleagues as much as 34 times per week per colleague. However, these averages do not reflect differences in how each person interacted with different colleagues. Every person had higher update frequencies for some of their colleagues as compared to others. The standard deviation of update frequency for each person reflects these differences in update frequency across colleagues, and ranges from 32 to 199; the higher the standard deviation of updating frequency, the more cliquish or skewed is the pattern of that person's direct and indirect contact with others. Average age of new information, on the other hand, is the average number of minutes it took for a person to get access to information from others, and this ranged from 104 minutes to 531 minutes. The distribution of this variable is skewed – while the mean average age of new information in the department is 251 minutes (it takes just over 4 hours to receive the updates that are transmitted), 75% have an average age of new information less than 275 minutes. One might consider people with average age of new information of 275 to 531 minutes as being less "in the loop" than others, since it takes longer for them to receive updates than others. Again, averages do not tell the full story, since they do not reflect the fact that each person would receive newer updates from some colleagues than others. Note that the newest information is always a direct interaction; by definition, a direct interaction is an update that is 0 minutes old. Thus, the age of information is driven by increases in the amount of time it takes for indirect contact to be "transmitted" across interactions to a person. The distribution of standard deviation of age of new information shows some people have very high differences in how soon they receive updates from some of their colleagues versus others. Since standard deviation measures tend to be correlated with averages, it is not surprising that the averages and standard deviations of update frequency and age of new information are highly correlated (.91 and .78 respectively).

FIGURE 7: DISTRIBUTION OF AVERAGE UPDATE FREQUENCY

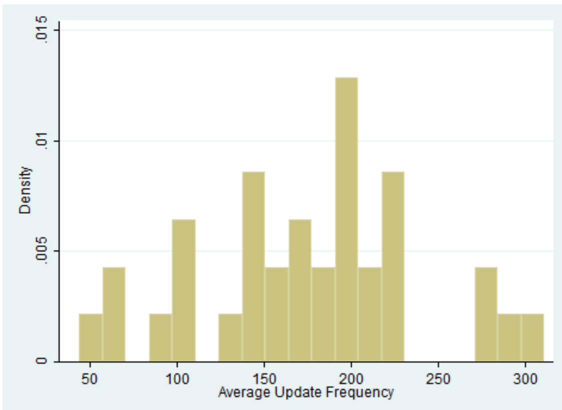


FIGURE 8: DISTRIBUTION OF STANDARD DEVIATION OF UPDATE FREQUENCY

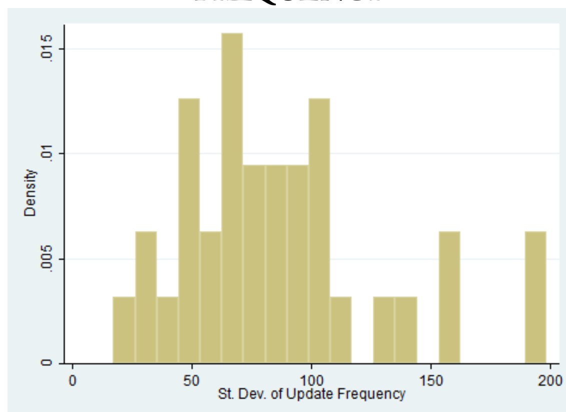


FIGURE 9: DISTRIBUTION OF AVERAGE AGE OF NEW INFORMATION

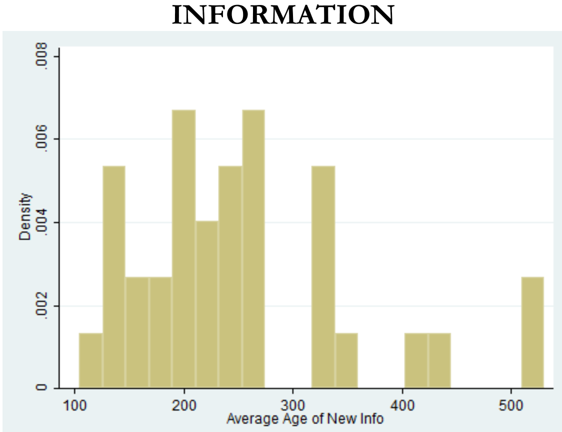


FIGURE 10: DISTRIBUTION OF STANDARD DEVIATION OF AGE OF NEW INFORMATION

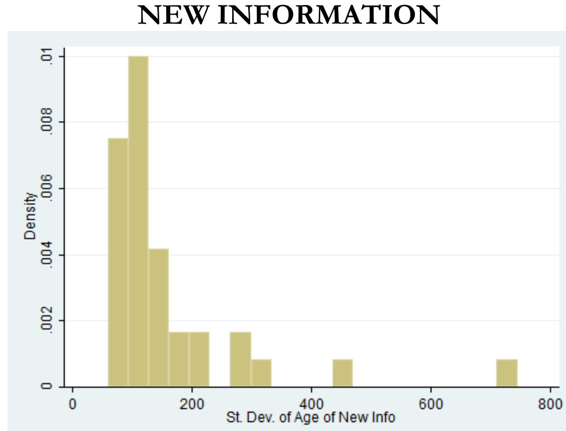


TABLE 10: DESCRIPTIVE STATISTICS AND CORRELATIONS FOR VARIABLES

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6
1. Daily Interaction Partners	17.414	2.661	11.926	21.865						
2. Daily Interaction Hours	2.098	0.901	0.606	4.339	0.61					
3. Average Update Frequency	179.667	61.749	64	311	0.68	0.91				
4. St. Dev. of Update Frequency	89.908	42.531	32.308	198.536	0.51	0.91	0.90			
5. Average Age of New Info	251.349	104.967	104.402	530.835	-0.53	-0.61	-0.62	-0.47		
6. St. Dev. of Age of New Info	155.702	131.784	58.527	744.389	-0.44	-0.51	-0.62	-0.39	0.78	
7. Contact Network Degree	22.357	6.184	1	28	0.24	0.10	0.06	-0.05	-0.29	-0.13
8. Contact Network Closeness	0.459	0.037	0.341	0.5	0.26	0.13	0.09	-0.03	-0.32	-0.15
9. Contact Network Betweenness	0.007	0.016	0	0.085	0.19	0.20	0.30	0.28	-0.24	-0.19
10. Contact Network Constraint	0.184	0.163	0.134	1	-0.29	0.05	0.04	0.19	0.03	-0.02
11. Advice Network (In) Degree	7.214	5.685	0	21	0.38	0.27	0.19	0.20	-0.10	-0.08
12. Advice Network Closeness	0.268	0.049	0.033	0.315	0.39	0.01	-0.01	-0.13	-0.04	0.01
13. Advice Network Betweenness	0.057	0.102	0	0.525	0.19	0.15	0.06	0.07	-0.09	-0.08
14. Advice Network Constraint	0.277	0.1	0.155	0.634	-0.10	-0.12	-0.07	-0.14	0.16	0.05
15. Male	0.576	0.502	0	1	0.01	-0.08	0.04	0.10	-0.13	-0.12
16. Manager	0.212	0.415	0	1	0.39	0.48	0.47	0.45	-0.37	-0.26
17. Tenure	16.662	7.535	0.83	30.83	0.06	0.06	0.11	0.02	0.07	-0.12

	7	8	9	10	11	12	13	14	15	16
8. Contact Network Closeness	0.99									
9. Contact Network Betweenness	0.31	0.37								
10. Contact Network Constraint	-0.79	-0.74	-0.12							
11. Advice Network (In) Degree	0.38	0.39	0.26	-0.29						
12. Advice Network Closeness	0.73	0.69	0.16	-0.94	0.53					
13. Advice Network Betweenness	0.23	0.25	0.05	-0.13	0.67	0.33				
14. Advice Network Constraint	-0.23	-0.24	-0.20	0.23	-0.71	-0.84	-0.46			
15. Male	-0.01	-0.01	0.16	0.11	0.27	-0.07	-0.11	-0.31		
16. Manager	0.30	0.34	0.49	-0.13	0.54	0.23	0.48	-0.25	0.15	
17. Tenure	-0.16	-0.16	-0.23	0.03	0.07	-0.01	-0.12	0.07	0.23	-0.07

In general, the amount of interaction hours a person had over the nine week period is very highly correlated with the new interaction measures (r=0.91 for average update frequency and standard deviation of update frequency, r=-0.61 for average age of new info, r=-0.51 for standard deviation of age of new info). This because the more interactions a person has, the greater that person's ability to receive updates, and the more quickly the person will receive those updates from others (decreasing age of new info). It is surprising that the interaction hours and average update frequency are so highly correlated, but this is likely because the department is small and has a considerably high amount of interactions among its people. On average, people interacted with 17 of their colleagues per day – approximately half of the department – and spent 2 hours per day interacting. Because of this very frequent direct contact, updates are transmitted quickly across the department, which means that each new interaction conveys many (indirect) updates. It is likely that if the department did not have such high interaction frequency and/or had more distinct cliques or sub-networks of individuals interacting, then the number of updates transmitted with each new interaction would vary more, resulting in a lower correlation between interaction time and average updating frequency.

Contrary to expectations, there is not high correlation (r=-0.01 to r=0.19) between the degree and closeness measures for the two networks and average updating frequency. The expectation was that as the number of contacts (degree) in the contact and advice networks increases, this should increase the number of people a person interacts with, thereby increasing the updating frequencies. Similarly, as the closeness of a person in the networks increases, this also increases the likelihood of directly interacting or indirectly having contact through an intermediary, thus increasing update frequencies. Yet this underlying logic is partially supported by the data. In fact, degree and closeness in both the contact and advice networks all have a moderate correlation (*r* ranges from 0.24 to 0.39) with the number of interaction partners per day. The number of daily interaction partners is in turn correlated (r=0.68) with average update frequency. Thus, even though there is not a high direct relationship between degree or closeness and average update frequency, the higher a person's degree or closeness in either social network, the higher the number of people the person actually interacts with, and the more people a person actually interacts with increases the average update frequency.

It was also expected that there would be a relationship between the network betweenness and constraint variables and average age of information – since each of these concepts captures how well a person has competitive advantage in gaining new information. Yet, the correlation between these variables is also relatively low. Note that betweenness decreases the age of information ($r= -0.09$ (advice network) and $r=-0.24$ (contact network)), since higher betweenness and lower age of information both mean higher competitive access to information, while constraint increases the age of information ($r=0.16$ (advice network) and $r=0.03$ (contact network)), since higher constraint and higher age of information mean less competitive access to information. While the signs of these correlations are in the expected directions, the strength of the correlations is lower than expected.

To further explore the relationships between each of these variables, OLS regression was performed on average update frequency, average age of new information, and the number of daily interaction partners. Table 11 shows the results of regression on average update frequency. Even after controlling for sex and managerial position, neither of the degree or closeness variables significantly affects average updating frequency. Managerial position is positive and significant in all but the last model, suggesting that managers have higher update frequency, and therefore greater exposure to others. The number of daily interaction partners also is positive and significant (Model 6), and when it is included in the analysis the R-squared increases to 0.507. Considering Table 12, which shows regressions on the number of daily interaction partners, there is marginal support for an effect of both social network degree and closeness in the advice network on the number of actual interaction partners on a daily basis. The more central a person is in the advice network, the higher the number of daily interaction partners. Managerial position and sex also matter, although their role is marginally significant. Women and managers have higher numbers of interaction partners. Approximately a third of the variance in average daily interaction partners is explained by network position, sex, and managerial position (R-squared of 0.345 and 0.325 in Models 3 & 5).

TABLE 11: OLS REGRESSION MODELS PREDICTING AVERAGE UPDATE FREQUENCY

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Male	-3.706	-18.888	-17.059	-18.906	-19.95	-0.165
	(20.046)	(21.483)	(22.434)	(21.497)	(21.414)	(16.232)
Manager	70.338**	74.078*	73.982*	74.435*	74.636**	35.773
	(24.235)	(26.793)	(30.604)	(27.192)	(26.109)	(21.324)
Contact Network Degree		-0.907				
		(1.807)				
Advice Network (In) Degree			-0.55			
			(2.329)			
Contact Network Closeness				-146.631		
				(308.702)		
Advice Network Closeness					-168.008	
					(222.601)	
Daily Interaction Partners						13.526***
						(3.292)
Constant	166.880***	203.434***	186.047***	250.416+	228.784**	-63.379
	(15.442)	(42.778)	(19.806)	(141.292)	(62.024)	(57.406)
Observations	33	28	28	28	28	33
R^2	0.22	0.256	0.25	0.255	0.265	0.507
Max VIF	1.022	1.104	1.531	1.136	1.063	1.21

Standard errors are in parentheses. Two-tailed tests for all variables.
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

TABLE 12: OLS REGRESSION MODELS PREDICTING NUMBER OF DAILY INTERACTION PARTNERS

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Male	-0.262	-1.576+	-2.037*	-1.573+	-1.475+
	(0.899)	(0.830)	(0.810)	(0.829)	(0.793)
Manager	2.555*	1.873+	0.918	1.826+	1.708+
	(1.087)	(1.035)	(1.105)	(1.049)	(0.967)
Contact Network Degree		0.051			
		(0.070)			
Advice Network (In) Degree			0.165+		
			(0.084)		
Contact Network Closeness				9.154	
				(11.907)	
Advice Network Closeness					14.348+
					(8.248)
Constant	17.023***	17.082***	17.521***	14.034*	14.351***
	(0.693)	(1.653)	(0.715)	(5.450)	(2.298)
Observations	33	28	28	28	28
R^2	0.156	0.257	0.345	0.258	0.325
Max VIF	1.022	1.104	1.531	1.136	1.063

Standard errors are in parentheses. Two-tailed tests for all variables.
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Finally, Table 13 shows results of regression on average age of new information. Here there is no support for a relationship between social network betweenness and average age of new information, nor was there support for a relationship between social network constraint and average age of new information. However, the number of daily interaction partners and the average update frequency significantly decrease the average age of new information. Average update frequency is the better explanatory variable, since when included, R-squared increases to 0.399 (Model 7).

TABLE 13: OLS REGRESSION MODELS PREDICTING AVERAGE AGE OF NEW INFO

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Male	-15.562	30.274	30.412	28.017	37.45	-20.256	-19.161
	(35.690)	(34.290)	(34.417)	(34.410)	(36.521)	(32.431)	(30.441)
Manager	-91.683*	-59.092	-84.912+	-73.394+	-67.144	-45.863	-23.372
	(43.147)	(46.351)	(46.328)	(41.069)	(42.436)	(42.607)	(41.624)
Contact Network Betweenness		-713.725					
		(1208.977)					
Advice Network Betweenness			104.651				
			(190.775)				
Contract Network Constraint				-16.356			
				(105.825)			
Advice Network Constraint					134.829		
					(187.849)		
Daily Interaction Partners						-17.930*	
						(6.577)	
Average Update Frequency							-0.971**
							(0.277)
Constant	279.756***	243.706***	238.141***	246.119***	200.056**	584.984***	441.825***
	(27.493)	(27.404)	(28.990)	(33.062)	(66.781)	(114.698)	(51.839)
Observations	33	28	28	28	27	33	33
R^2	0.145	0.144	0.143	0.133	0.157	0.319	0.399
Max VIF	1.022	1.349	1.329	1.032	1.169	1.21	1.308

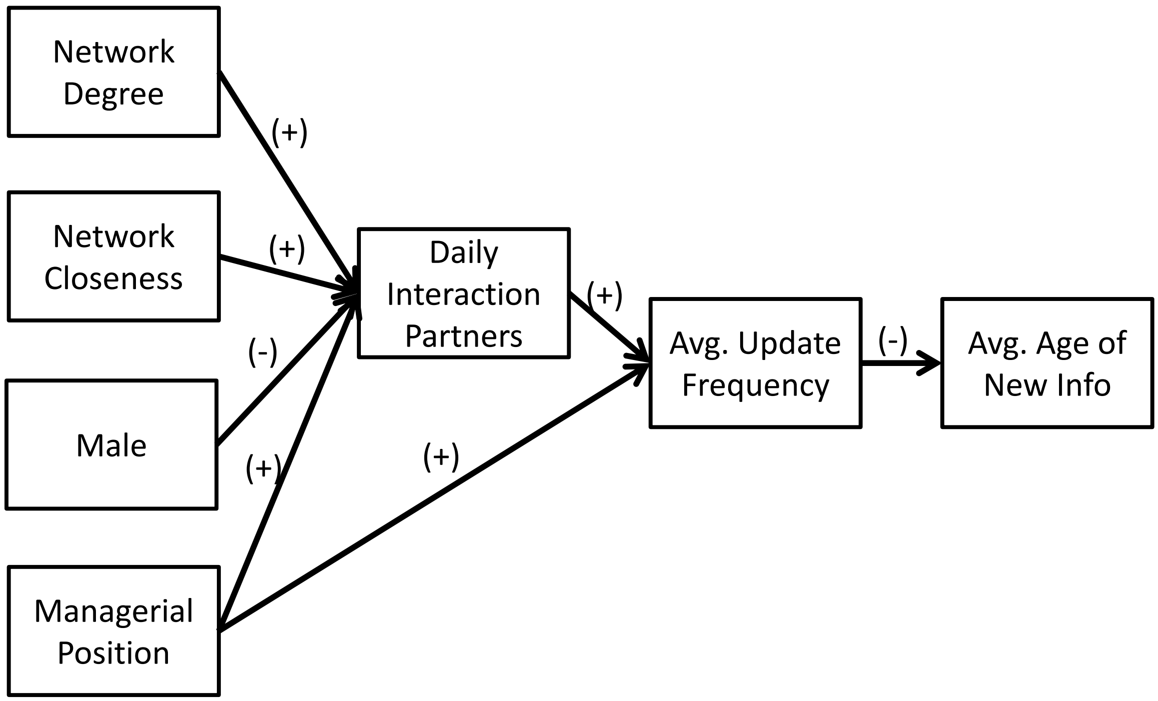
Standard errors are in parentheses. Two-tailed tests for all variables.
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

DISCUSSION

Overall, results indicate an interesting relationship between network position and the new interaction measures. In this dataset there is only a very weak direct relationship between network position and both average update frequency and average age of new information. This is likely because both social networks, the contact network and the advice network, reflect relationships which have been accumulated over a longer time period than the interaction data collection. The number of actual daily interaction partners is a better predictor of average update frequency, although how many people one interacts with on a daily basis is affected by one's closeness and degree centrality. People who are more highly connected to others in social networks are more likely to actually interact with more people, and this leads to higher exposure to others through interaction (both direct and indirect). Further, the data indicate that the best predictor of average age of information is average update frequency – those who have higher exposure to others through interaction also have the newest information.

These relationships are reflected in Figure 11, which shows a path model of the variables, including the control variables (sex and managerial position). The current dataset does not have enough observations to test this path model, so the results here are suggestive. Further research should confirm whether or not this model is appropriate. However, there is significant theoretical justification for the model. First, network position should influence actual interaction patterns. One of the major mechanisms posited for why social networks matter for individual outcomes is that the relationships in networks reflect actual patterns of communication, providing advantage in information access. Among the various network centrality measures, the measures which are most likely to affect direct interaction with others are degree and closeness. Both how many direct partners one has in a network and how close one is to all others in a network should affect the number of people with whom one interacts. That is, one is more likely to interact with people one is socially closest to, direct partners being most likely.

FIGURE 11: MODEL SUGGESTED BY THE RESULTS, TO BE CONFIRMED BY FUTURE RESEARCH



Yet the interaction measures are not mere reflections of social network centrality. The people one interacts with include not just those one has a relationship with, but also various other people, and is affected by demographics – such as sex – and the demands of one's position or job requirements. Additionally, the amount of exposure one receives to others through interaction (average update frequency) is affected not just by how many people one interacts with, but by how those interactions accumulate over time, given the specific temporal ordering of interaction which has occurred. Measures of social network centrality such as betweenness and constraint are conceptually measures of competitive access to information, but rely on the assumption of consistent information flow across relationships. The average update frequency and average age of new information measures, on the other hand, calculate this enhanced access to information taking into account variation in communication patterns within and across relations, as well as the temporal ordering of those communication events.

While the average update frequency and average age of new information are conceptually distinct – one relates to how much information one has access to and the other relates to how quickly one can receive that information – empirically these are related (r=-0.62). The more information one has access to, the newer that information will be, particularly within a small social environment with frequent interactions such as at ManuCorp. High correlation among variables is a frequent difficulty in social network research. For instance, degree and closeness here are also highly correlated (r=0.99 in the contact network and r=0.53 in the advice network).

Future research should explore whether the relationship between average update frequency and average age of new information remains as strong in a variety of other social contexts, particularly in environments with less frequent interactions and with more disconnected actors or subcliques. Additionally, future research should explore whether in other environments the relationship between average update frequency and interaction time decreases.

CONCLUSION

This study integrates the insights that the order of communication (Moody 2002) and the amount or frequency of communication (Aral and Alstyne 2011) are crucial to understanding how information is transmitted. The interaction analysis presented opens up new possibilities for future research seeking to understand how network benefits such as access to information and the timeliness of information depend on day-to-day interaction and communication events. Analyzing data on interactions reveals flows of information not represented by social network structure. In other words, two people with the same social network centrality *can* have differing rates of access to and timeliness of information, due to different choices about and constraints on interpersonal interactions. People vary in how they activate their social networks in everyday interactions (Smith, Menon, and Thompson 2012), and this affects how much information they actually receive.

Using this approach, time remains continuous – the researcher does not need to artificially divide the data into discrete period such as months, weeks, or days, in order to analyze information flow over time. This method of processing time-ordered communication data can be applied to any kind of social behavioral data collected about people – from physical interactions to phone calls, to email messages, to instant messages and Facebook updates. This is especially useful when one has data on who has communicated with whom, but not the content of that communication. To an increasing degree, data on communication is available to researchers, but privacy concerns often require content to be removed. This method allows us to better understand the ways in which information flows through a network of people, given the constraints (time, space, scheduling norms, and organizational/work rules) that affect how people contact their alters on a daily basis.

Moreover, the contribution of interaction analysis is not just that it allows greater precision in measuring information flow in groups. More than this, it allows researchers to distinguish between a person's *potential* network benefits and *activated* network benefits. A person's position within the structure of relations, for example network centrality, indicates his or her potential to receive resources. Yet a person's access to and timeliness of information from realized interactions reflects his or her activated network benefits. By distinguishing between potential and activated network resources, future research can ask questions such as: When do peripheral (low centrality) actors obtain information which allows them to become successful and subsequently more central? How do central actors maintain – or lose – information advantages over others? These and other questions will allow social network research to better account for individual action (both agentic and constrained) in network outcomes.

Chapter V: Knowing Your (Relationship) Strengths: The Effect of Social Information Flow on Relational Acumen (Paper 3)

SUMMARY

The network activation literature has given us the insight that how networks are enacted matters -- important resources and information may not be accessed by individuals when they do not realize (or misjudge) whom to ask for help. This highlights the importance of relational acumen, the ability to accurately judge one's relationships. I propose that those who have higher and more efficient (less redundant) access to social information have greater relational acumen, since social information facilitates interpretation of the meaning and strength of one's relations. Typically, access to social information is measured via network centrality and constraint. However, network contacts, which are stable relationships, are imprecise for measuring access to day-to-day social information flows. I therefore develop a method for measuring access to social information using face-to-face interaction data. Results from an administrative department within a manufacturing company highlight that a) in general, people do not have very high relational acumen, b) network constraint (as measured by surveys) contributes to explaining relational acumen, c) however, face-to-face interactions are a considerably greater determinant of relational acumen. How efficiently one's interactions provide access to information is key – relational acumen is enhanced most when a person interacts with people who can convey novel information from prior interactions.

INTRODUCTION

Networks have long been known to provide an important source of information and resources (Burt 1992; Granovetter 1974; Podolny and Baron 1997). Recently, studies have explored how people actually use their networks, highlighting that not all relationships convey information and resources. Network ties must be activated to provide the benefits that a person seeks, and many ties are not activated. For instance, job seekers must think of whom to contact to ask for information about job openings and referrals. However, job seekers only think of a subset of their contacts to reach out to for information (Smith, Menon, and Thompson 2012). In general, when people need help, they turn to a limited set of close contacts for it (Fischer 1982; Hurlbert, Haines, and Beggs 2000). Once a person thinks of ties which could be helpful, those ties must be mobilized, meaning they must be contacted and asked for help. Sometimes, mobilization attempts fail, such as when contacts decide that they do not have enough trust in the person to take the risk of helping (Smith 2005).

It is not surprising that not all of a person's contacts are useful when that person needs help. After all, activating contacts takes time and effort. Scheduling time to talk to all of one's contacts can be difficult, especially weak contacts that one infrequently sees. As a result, it makes sense that not all of one's contacts will be active at any one time. In addition, the expectation that not all of one's contacts *will* be helpful would lead a person to be selective in activating ties. For instance, a very weak tie is less likely to provide intense emotional support, and a very strong tie is less likely to provide new information about job leads that one hasn't heard before (Granovetter 1973). Intuitively, a person who seeks help will consider his or her relations and make a judgment about whom to contact based on an expectation of who is likely to be helpful.

However, these expectations about who will be helpful may or may not be correct. When a person decides not to contact someone who would have helped, this is a missed opportunity. Conversely, when a person attempts to get help from a contact who is reluctant or can't help, this is wasted effort. The possibilities for missed opportunities and wasted effort point to the importance of a person's judgment when evaluating his or her ties. Reaping the full benefits of one's network requires exercising good judgment in choosing whom to ask for help. To a certain degree, this judgment involves estimating who is likely to have access to the resources one needs – such as job information, cash resources, or other knowledge, as the case may be. However, perhaps more importantly, judging whom to ask for help involves judging the quality of the relationship one has with each person. People with whom one is very close are willing to provide different kinds and levels of help than people with whom one is not close (Wellman and Wortley 1990). Therefore, knowing which of one's contacts are weak versus strong ties is important in efficiently making use of one's network.

This paper defines relational acumen as the ability to accurately perceive the strength of one's relations, which is an important skill needed for obtaining network benefits. The paper attempts to make two related contributions: First, drawing on the literature on network perception, it argues that relational acumen is developed as a result of enhanced access to social information in a given social context. Second, it proposes a method for measuring that enhanced access to information, when data on participants' actual interactions are available. By using the realized pattern of face-to-face interactions, we can account for the dynamic contextual and temporal factors that alter how information flows in enacted networks. To test these arguments, I use a comprehensive and longitudinal dataset on patterns of interaction and networks in an administrative department of a manufacturing corporation. A radio frequency identification (RFID) tracking system was installed at the worksite, permitting precise measurement of real-time interactions over a nine week period. Results show that having efficient interactions -- those which provide the most social information with the least amount of time interacting -- do indeed increase relational acumen. Further, this measure of access to information, derived from interaction data, is a more significant driver of relational acumen than traditional network measures. These findings highlight the importance of examining the day-to-day activation of networks. How people benefit from their networks varies depending on how they (and those around them) activate their networks over time.

RELATIONAL ACUMEN

"Years ago, I was discussing the various relational conflicts occurring in our workplace with my former boss... He shared somewhat smugly that he got along well with everyone in the organization.... From his perch, others were struggling with their work relationships. From his perspective, he was getting along splendidly with others. A poll from other perches in the company would have spilled out… a differing perspective about his relational acumen."

– Susie Amundson, www.wiseatwork.net[13]

Relational acumen has a lay meaning of being perceptive or knowledgeable about one's relationships with others. In colloquial terms, a person with high relational acumen is someone who is skillful in assessing the quality of his or her relations – seeing those relationships as they really are, rather than with an overly rosy positive bias, as in the quote above. In other words, relational acumen comes from one's ability to "read" relational

[13] http://wiseatwork.net/2011/03/02/the-main-thing-about-workplace-problems-2/. This quote is an example of the lay usage of the term relational acumen.

partners and understand, from their perspectives, how strong one's relationships with them are.

Thus, I define relational acumen as the ability to accurately perceive the strength of one's relations. Relationship strength is a key aspect of the quality of a relationship because it guides how the relationship is conducted (what behaviors are expected within the relationship) and as a result, what instrumental and expressive benefits are available from that relationship. Strong relationships are those with higher levels of closeness and emotional intensity (Marsden and Campbell 1984); these relationships have higher levels of trust, and are more likely to involve frequent interaction. As a result, strong relationships convey social support (Wellman and Wortley 1990). By contrast, weak relationships are those that involve less closeness and often involve people who see each other infrequently. Because parties in weak relationships communicate less often, they are likely to be part of different social circles, and therefore are able to convey novel information (Burt 1992).

Both weak and strong relationships can provide important benefits. However, misjudging the strength of one's relationships can result in wasted effort and missed opportunities. Turning to a weak relationship for emotional support, for example, is more likely to result in disappointment and wasted effort, since weak ties do not have the same disclosure of personal information and creation of trust that strong ties have. Similarly, asking a weak contact for a personal loan or favor that involves putting his or her reputation at risk is not likely to be met with success; this is because weak ties lack the shared ties that provide the ability to monitor each other's good behavior (Coleman 1988; Smith 2005). Also, wasted effort can occur when seeking novel information from strong relationships, since it's likely that one would already have access to the information the strong contact has

(Granovetter 1974). Moreover, believing that a tie is weak, when in fact the other person believes it is strong, can lead to missed opportunities for receiving social support.

Since relational acumen is defined as an individual-level measure of accuracy in perceiving relationships, it is important to be specific about how accuracy is determined. What is the standard against which a person's perceptions of relationship strength are to be compared? Typically, in social network research, determining whether or not a relationship exists involves confirming whether both parties to a dyad agree that it does. This is because there often is not an "objective" source of information about relationships. Relationships are subjective experiences; each person in the dyad is entitled to his or her own opinion, and neither one is more authoritative than the other.

Mutual agreement, then, is the best way of determining whether a person's perceptions are accurate. This is doubly true when determining the accuracy of perceptions of relationship strength – the closeness or emotional intensity of the relation is a subjective experience that can only be assessed by the parties involved. There are two ways to have accurate perceptions about one's relationships, however: by accurately perceiving that a relationship is strong (both agree that the relationship is strong), and by accurately perceiving that a relationship is weak (both agree that the relationship is weak). A person misjudges relations, and therefore has lower relational acumen, when he or she believes that relations are strong while alters believe that the relations are weak, or when he or she believes that relations are weak while alters believe that the relations are strong. Because relational acumen is at the individual level, rather than the dyadic level, it captures the ability of a person to understand which relations are closer relations. Or, put differently, it captures the skill of a person in differentiating which of his or her contacts are willing to *be* emotionally close or not.

Relational acumen is different from other forms of perception accuracy studied in the social network literature which focus on biases in the recall of ties and contact frequency (e.g. Freeman, Romney, and Freeman 1987). For example, studies have shown that people are more accurate in recalling with whom they had contact when the contact involved more close relations and people with whom they had more recent contact (Marsden 1990). However, these studies focus on measuring accuracy of perceptions against an objective measure, such as contact frequency. By contrast, relational acumen is a form of meta-perception – it is the accuracy of one's perceptions about alters' perceptions. As such, it involves making meaning of a variety of social signals conveyed by alters. This includes interpreting alters' actions, communications, emotions, and attitudes, all with the goal of understanding how alters view their relationships with oneself. A person with high relational acumen is able to interpret these social signals to better understand when people feel close to him or her or not.

Theory: Relational Acumen, Network Perception Accuracy, and Social Information Flow

Relational acumen is a form of what has been called "network perception accuracy." The network perception accuracy literature has explored people's ability to correctly identify which friendship or advice ties exist in their social environment. Network perception accuracy has been shown to lead to power within organizations (Krackhardt 1990), since the more accurate one's perceptions of the social network as a whole, the better one can identify structural holes, influential actors, and boundaries between political factions. Since this kind of accuracy refers to perceiving the existence of ties, it is not the same as relational acumen – which focuses on perceiving the strength of ties. However, network perception accuracy and relational acumen are related constructs, and it is reasonable to expect that similar mechanisms operate in both.

Like relational acumen, network perception accuracy depends on interpreting complex social cues. Having an accurate understanding of which friendship and advice ties exist in a social network requires both observing others – interpreting their attitudes and behaviors towards each other – as well as hearing what other people say about how they get along. In fact, what other people say about relationships, what one "hears through the grapevine," is an important determinant of one's mental map of the network. In other words, what one knows about others' relationships is affected by the social information that one receives from one's contacts (Krackhardt and Kilduff 1990).

Social information, which is information about the attitudes, behaviors, and relationships of others, is conveyed from person to person. An extreme form of this is gossip, which is the purposeful transmission of information about others' behaviors and relations. Social information also includes "water cooler" talk, or causal conversations where stories about events and people are conveyed, providing participants with information about the social environment of the group – who is working with whom, who is friends, etc. Social information is also conveyed between individuals in order to accomplish work. For instance, imagine that a colleague advises one to submit a proposal first to Edward, because if Edward agrees with the proposal then his partner Jacob will quickly follow suit. The social information included in this advice indicates that Jacob and Edward likely have a positive working relationship and that Jacob trusts Edward's judgment.

Yet, social information, like its extreme form gossip (Burt 2000), is often imprecise. What if Jacob and Edward are instead rivals, calling into question the colleague's belief that Jacob will agree with Edward's actions? Simply having access to some social information then does not produce accuracy in perceptions of relationships. Instead, what is needed is access to higher levels of social information, from a variety of sources, so that one can compare pieces of social information, testing one against another to produce a more accurate mental model of the network.

Confirming this line of argument, studies of network perception accuracy have shown that people with greater access to social information are indeed more accurate in their perceptions of others' relationships (Bondonio 1998; Casciaro 1998; Casciaro, Carley, and Krackhardt 1999). However, relational acumen concerns one's perceptions of one's own relationships, rather than relationships between other people. Is social information similarly needed for interpreting ego relations? I argue that when interpreting the quality or strength of one's own relations, social information continues to be important.

First, while a person can directly observe the behaviors of others towards himself or herself, these behaviors require social information to interpret in context. For example, if a person receives a birthday gift or other token of affection from a colleague, the person may think the colleague is treating the relation as a strong one. However, this interpretation can change if one hears that the colleague gives birthday gifts to everyone in the office as a habit. The social information one receives about others helps one gauge the meaning of the behaviors one directly observes.

Second, it can often be difficult to interpret another person's intentions, even when their actions are understood in context. Impression management attempts (Leary and Kowalski 1990) can make an alter seem to want a stronger and more trusting relationship than he or she truly feels. A supervisee may want a supervisor to believe that their relationship is a close one for instrumental purposes, even if the supervisee does not feel especially emotionally close to the supervisor. In situations such as this, higher access to social information from third parties can be helpful for providing confirming or competing evidence. The supervisor might hear through third parties whether the supervisee continues to act like the supervisor's friend when he or she is not around, for instance.

In summary, higher access to social information should increase a person's relational acumen. The more social information one receives, the better one can interpret the behaviors and intentions of others, allowing one to more accurately interpret the strength of one's relations.

Proposition 1: Higher access to social information increases relational acumen.

However, there is a cost to receiving higher levels of social information. This cost is the substantial amount of time it takes to have conversations which communicate social information and in general the effort it requires to maintain the relationships which provide social information. Moreover, just receiving a greater amount of social information does not always result in more accurate information. Inaccurate information can be amplified within social circles when the same information is told and re-told between people (Burt 2000). Therefore, what is most beneficial is efficient access to information. When one reduces the redundancy of information (receiving the same information more than once), one reduces the time it takes to acquire the social information as well as improves its value (Burt 1992). As a result, I propose that one's efficiency of access to information improves one's ability to better interpret the strength of one's relations.

Proposition 2: Higher efficiency of access to social information (decreasing redundancy of information) increases relational acumen.

Thus far, this paper has argued that social information matters for people's interpretations of the strength of their relations. The idea of information flowing through a social context, from person to person, is not a new one. Social network analysis is built on the premise that information does get transmitted from one person to another, and that a person's position in the network determines his or her access to information. In the next section, I therefore briefly develop specific hypotheses, using a network approach to implement Propositions 1 and 2. However, I then review recent literature which has called into question the ability of social network analysis to precisely measure information flow, given the complexities of timing, scheduling, and spatial constraints on interaction. Social network analysis may not reflect information flow as it happens in real life. I then develop a different approach to understanding information flow, based on analysis of interactions. This new approach maintains the spirit of network analysis – that information is conveyed from one person to another – but assesses patterns of interaction as they happen in a particular context. Using this approach, I next develop specific hypotheses implementing Propositions 1 and 2. I then empirically test these hypotheses with network and interaction data collected at the study site.

Access to Social Information: The Social Network Approach

The social network approach asserts that networks are stable structures over time that convey information and resources (Burt 2005; Granovetter 1974). Specific relationships between people are pipes, or conduits, that funnel information from one person to another. When all relationships are considered together, they generate a network: like a map of a transportation system, a network shows how information can move from one location to another.

In this approach, how central a person is in the network determines how much information that person can receive from others. A person who is central acts as a transportation "hub" for information, able to intercept and convey more information than others. While there are multiple ways of measuring centrality (Wasserman and Faust 1994), the simplest and perhaps most popular measure is degree centrality. Degree centrality is the number of contacts a person has. Conceptually, using this form of centrality is appropriate when it is believed that the amount of information one receives is proportional to the number of one's sources of information. Existing studies of network perception accuracy use degree centrality to measure access to social information, and consistently find that the greater the number of contacts a person has, the more accurate is his or her perception of ties between others (Casciaro 1998; Bondonio 1998). According to the arguments in the prior section leading to Proposition 1, access to social information not only increases accuracy in perceiving others' ties, but should also increase accuracy in perceiving the strength of one's own relations. Therefore, the more contacts a person has, the higher his or her relational acumen should be.

Hypothesis 1: Network degree centrality (higher access to social information through contacts) increases relational acumen

On the other hand, the assumption that the amount of social information one receives is proportional to the number of relationships can be questioned. If one's contacts are redundant – they have relationships with the same third parties – their value for providing new information is lower. In network terms, redundancy is measured via constraint (Burt 2004). People who have more constrained networks have more redundant contacts, which reduces their access to useful social information, and lowers relational acumen.

Hypothesis 2: Network constraint (increased redundancy of information) decreases relational acumen

The previous hypotheses are built on the foundation of decades of network research showing that centrality and constraint are important determinants of outcomes for individuals and organizations. However, recent work has begun to call into question whether long-term structures of relations can provide an accurate measure of information flows in day-to-day life. These challenges focus on the role of communication frequency, scheduling constraints, and sequencing constraints on information flow.

First, communication between people varies highly. Communication varies not just across relationships, but also within relationships over time. Using email data, Aral and Van Alstyne (2011) found that weak ties provide potential access to novel information, but the actual novel information received depends on a) how frequently people communicate to transfer that information and b) aspects of the environment such as how quickly information is generated. In some environments, it is relations with high communication frequency ("strong ties") which actually provide the most novel information. Aral and Van Alstyne's findings highlight that the choices people make about when and how often to communicate – how they enact their relations in real-time – can alter how information flows from person to person.

Second, the physical reality of not being able to be in touch with all of one's contacts at once can change information flows. Gibson (2005) used a simulation model to illustrate that scheduling constraints (such as being able to meet with only one alter at a time) significantly affect diffusion. While actors with many relations act as "hubs" or "super-spreaders" of information in network analysis, schedule constraints can actually make such actors bottlenecks, preventing information flow until they can manage to meet with enough of their alters. The implication is that when central actors become bottlenecks of information, measures of centrality and constraint become inaccurate as measures of access to information.

Finally, the sequencing or temporal ordering of communication flows through a network matters. Morris and Kretzschmar (1995; 1997) and Moody (2002) have demonstrated that diffusion is affected by assumptions about whether relationships are concurrent or sequential. To take an example, suppose Annie interacts with Barry, but does not interact with Barry again. After that interaction, Barry interacts with Charlie. As a result of the time ordering of these interactions, Annie → Charlie is a possible path for information flow, meaning Charlie can learn information originating from Annie, as a result of interacting with Barry. However, the reverse is not true. Because Annie stopped interacting with Barry, Annie cannot learn any information originating from Charlie. Thus, only knowing that Annie has a relationship with Barry and Barry has a relationship with Charlie is not enough to understand the direction of information flow, if interactions are not concurrent.

Access to Social Information: An Interaction Approach

Given the preceding concerns about social network analysis, what is needed is a way to more directly assess information flow in networks that takes into account variance in communication frequency and the realities of physical and temporal constraints on information flow. The crucial element that matters for access to information is interaction. Whether interaction happens in person or via electronic media, this interaction is necessary for people to exchange information. How people enact their networks, activating some relationships but not others (Smith, Menon, and Thompson 2012), or by being bottlenecks or information hubs (Gibson 2005), can be taken into account by analyzing the actual interactions that they have in context.

This requires more granular and precise information on people's interactions. Archival email data, cell phone data, and electronic movement tracking systems provide such information, and they are increasingly used to assess the existence of relations and extent of communication between individuals (e.g. Waber et al. 2011; Wu et al. 2008). However, I argue that taking full advantage of this specific time-ordered data requires a shift in the conceptual focus of analysis.

Rather than conceptualizing relationships as stable conduits of information, I argue that the focus of analysis should be on conceptualizing the movement of specific flows from person to person as a result of chains of interactions. A full description of interaction analysis is presented in Paper 2 of this dissertation (See Paper 2 and Appendix 2). The method is designed for instances where the researcher has specific data on who interacted with whom, and at what time, but without knowing what was discussed. While it is ideal for the data to include the content of interactions, such as topics of conversation, this is often not possible. Therefore, the method assesses who receives exposure to others, providing the opportunity to convey information. As repeated interactions happen over time, new exposures to others are considered "updates" of information. The higher the updating frequency a person is calculated to have, the more that person has exposure to a higher level of information flow.

Interaction analysis is similar to social network analysis in assuming that information is transferred between individuals. However, the advance that interaction analysis provides is that it does not assume that the same level of interaction occurs in different relationships, or that that the same level of interaction occurs within a single relationship over time.

Moreover, interaction analysis incorporates the sequencing of interactions in the calculation of updating frequency. As a result, interaction analysis should provide a more precise estimate of a person's access to information flow. It takes into account the fact that people vary in how they enact their networks, activating some ties, but not others, at various moments in time.

Recall Proposition 1, which asserts that those who have higher access to social information should have higher relational acumen. Implementing this proposition with an interaction analysis, the hypothesis becomes that those who have higher levels of updating frequency (more exposure to others' information) are better able to interpret the strength of their relations.

Hypothesis 3: Higher updating frequency (higher access to social information through interactions) increases relational acumen

As argued earlier, simply having more information is not necessarily best. More efficient access to information, on the other hand, is valuable. The calculation of updating frequency already reduces the redundancy of information (and must do so given the assumptions of the model). However, it does not take into account the time spent interacting. Time spent interacting is an important cost to gathering social information, particularly in an organizational setting, where employees are often under pressure to accomplish work quickly. Spending less time interacting, while maintaining a high level of exposure to others' information, places pressure on a person to communicate more selectively. For example, having reduced time for water cooler talk means that more of the relevant social information is the focus of conversation (Edward and Jacob had an argument, and so they are less likely to jointly support a proposal), instead of information that may be fun but unnecessary (perhaps gossip about Edward's long work hours). Proposition 2 then implies that the more efficient a person's interactions are, producing higher updating frequency with less time spent interacting, the more accurate the person will be in interpreting the strength of his or her relations.

Hypothesis 4: Higher interaction efficiency increases relational acumen

METHODS

Data

This study uses data collected at ManuCorp in all three phases. This includes the contact network at Time 1 (n=33), interaction data at Time 2 (n=34), personality data at Time 3 (n=32), and revised relationship strength ratings at Time 3 (n=33). Data from twenty-six individuals are available from all of these sources[14].

Dependent Variable

Relational Acumen at Time 3: Relational acumen is the accuracy with which a person perceives the strength of his or her relations. It is calculated as the correlation between a person's responses indicating how strong a relationship they have with each other person and others' responses indicating how strong a relationship they have with that person, both on a scale of 0 to 5. 0 = No relationship, 1 = I prefer to avoid this person[15], 2 = Weak, 3 = Somewhat weak, 4 = Somewhat Strong, 5 = Strong.

This variable is an individual level measure of how well a person understands how others relate to him or her. Theoretically, the measure has a range of -1 to 1, although usually it should be above 0 (indicating a positive correlation between a person's assessments

[14] This increases to twenty-seven when personality data is not required in the analysis.
[15] Whether "prefer to avoid" should have a higher or lower value than "no relationship" is unclear. However, in this dataset, only one person chose to use the "prefer to avoid" category – and just for one relationship. Thus, the coding of "prefer to avoid" versus "no relationship" is inconsequential.

and his or her alters' assessments of the person's relationship with them). In prior studies, individual level accuracy about the existence (rather than strength) of ego relationships has varied considerably within sample populations: In Casciaro, Carley, and Krackhardt's (1999) sample, accuracy in perceiving ego advice ties averaged 0.44, with a standard deviation of 0.29. Accuracy in perceiving ego friendship ties was similar on average (0.41), with a smaller standard deviation of 0.19. By contrast, their study participants' accuracy in perceiving other people's relationships (non-ego ties) varied to a lesser extent – a standard deviation of 0.12 for both advice and friendship ties. As a result, the available evidence indicates that accuracy in reporting one's own relationships varies even more than accuracy in reporting others' relationships. We should expect that relational acumen will also vary meaningfully from person to person.

Independent Variables

Network position at Time 1: The contact network was constructed using the survey data at the beginning of the study. A relationship is considered to exist based on mutual consensus – it exists if both individuals in the dyad reported knowing each other (regardless of whether the relationship was weak or strong). Degree centrality is the number of relationships a person had in the contact network. Constraint was calculated with the igraph package for R, implementing Burt's (2004) measure of constraint.

Interaction Analysis Measures at Time 2: Updating Frequency was calculated using the method outlined in the Appendix. Creating a measure of interaction efficiency (increases in updating frequency relative to the time spent interacting) is not straightforward; this is because time spent interacting is itself an important driver of updating frequency. In general, in order to receive more updates, a greater number of interactions have to occur, increasing total interaction time. However, the idea captured by interaction efficiency is that increasing levels of updating frequency, while holding constant interaction time, is more beneficial. Therefore, to directly measure this efficiency, I orthogonalized the updating frequency variable from a measure of the total number of hours a person interacted with others over the course of the observation period. Orthogonalization is a procedure which removes shared variance by regressing one variable on another; the new variable (interaction efficiency) is the residual of updating frequency after subtracting the expected level of updating frequency, given the total interaction hours. It is the degree to which a person receives more exposure to others' information (updating frequency) than expected, given his or her amount of interaction with others. In other words, comparing two individuals with the same amount of interaction time, the person with higher updating frequency has had interactions which have generated higher exposure to others' information. That person has higher interaction efficiency.

Examples: Martin & Tom

Thus far, however, the idea of interaction efficiency remains abstract. Before proceeding with the analysis and results, it is helpful to make the difference between high and low interaction efficiency more concrete with examples from two individuals in the data. This will provide a more intuitive understanding of interaction efficiency. These examples also help demonstrate that the interaction efficiency measure is capturing a meaningful difference in participants' interaction patterns.

Both Martin and Tom are good-natured and "easy to get along with" colleagues.[16] Both consider themselves extraverts (on a 1 to 7 scale of extraversion, Tom rated himself a 6 and Martin rated himself a 6.5), and the amount of time they spend interacting with others on a daily basis is comparable. Yet, they differ dramatically in their interaction efficiency: Tom has the lowest interaction efficiency score of the group, and Martin has one of the highest.

On a typical day, Martin and Tom spend over 2 hours in interactions with others. To see how these two men interact differently, I discuss a comparable day for each of them. On September 30th, Tom interacted with others for 158 minutes. During the course of that day, he interacted with 13 individuals, via a total of 50 distinct interactions. On October 1st, Martin's experiences were comparable. He spent 159 minutes engaging others in interaction. While he had fewer distinct interactions (24) than Tom, he also only interacted with 13 individuals over the course of the day.

These two days, 10/1 for Martin and 9/30 for Tom, are comparable because they had the same amount of interaction time and the same number of interaction partners. However, the patterns of interaction were quite different from each other. Table 14 summarizes all of Martin's interactions for the day. It shows that as Martin interacted with each person throughout the day, he was able to obtain exposure to many other people. When Martin first arrived in the morning and interacted with Roseanne, he gained exposure to twenty-one individuals, plus Roseanne herself; this is because Roseanne had interacted with others prior to Martin's arrival. Similarly, Edward, Diane, Travis, Alice, and Victor –

[16] I draw here on observation of their interactions with others, comments others have made about them in interviews, as well as my own interactions with them. In my observation notes, the interactions of both Martin and Tom involved a combination of serious discussion, playfulness, and laughter. They both engaged in not just work-related discussion but also personal discussion (kids, hobbies, weekend activities). In other words, neither individual was withdrawn or avoided interaction with others.

Martin's subsequent interaction partners – are able to provide Martin with much new exposure to others. Even when Martin has repeated interactions with the same person during the day, the repeat interactions continue to convey new exposure. For example, Martin interacts with Alice at 9:14 AM (providing Martin exposure to 9 other individuals aside from herself) and then again at 9:40 AM (providing Martin exposure to 16 other individuals aside from herself). The second interaction with Alice is not redundant, because between 9:14 and 9:40, Alice has interacted with other people. So when she rejoins with Martin at 9:40, she conveys new updates to him.

TABLE 14: MARTIN'S INTERACTIONS ON 10/1

Interaction Partner	Beginning of Interaction	Updates (exposure to others) available through interaction
Roseanne	8:04:40 AM	22
Edward	8:33:31 AM	26
Diane	8:46:41 AM	10
Travis	9:11:07 AM	11
Alice	9:14:41 AM	10
Alice	9:40:11 AM	17
Victor	9:46:29 AM	17
James	9:58:26 AM	7
Dan & Erin	10:04:27 AM	10
Diane	10:04:34 AM	4
Lara	10:06:10 AM	11
Dan	10:13:21 AM	4
Travis	10:46:22 AM	17
Alex	10:48:49 AM	14
Travis	10:53:20 AM	1
James	12:56:27 PM	27
Kirk	1:01:12 PM	19
Roseanne	1:01:37 PM	8
Alice	2:00:01 PM	20
Harry	2:19:17 PM	2
Alice	2:29:17 PM	1

* The way to read this table is the following: At 8:04 AM, Martin interacted with Roseanne, and Roseanne provided Martin exposure to 22 individuals (including herself); about half an hour later (8:33 AM), Martin interacted with Edward, who provided Martin new exposure to 26 individuals (including himself); and so on. Note that at the end of the day, Alice has a repeat interaction with Martin at 2:29 PM, and can only provide Martin with new exposure to one person (herself).

By contrast, Tom's interactions do not provide quite as much new exposure. Table 15 provides all of Tom's interactions. Some of Tom's interactions do provide high levels of exposure. For instance, when Tom arrives in the morning and interacts with Jane, she provides exposure to 21 other individuals. However, Tom's next interaction is with Edward, who can only provide Tom exposure to four additional people, aside from himself. Why? Because Edward and Jane had recently interacted with some of the same people. So

Edward's exposure to others in the department was mostly redundant with Jane's. Throughout Tom's busy day, several people interact quite often with him, including Jane, Hector, and Erin. Yet their interactions bring Tom fewer updates, because they are not interacting with very many other people in between meetings with Tom. In fact, when they are not meeting with Tom, Jane, Hector and Erin are often meeting with each other and a small set of nearby co-workers.

TABLE 15: TOM'S INTERACTIONS ON 9/30

Interaction Partner	Beginning of Interaction	Updates (exposure to others) available through interaction
Jane	8:30:39 AM	22
Edward	8:46:11 AM	5
Edward	8:51:40 AM	2
Jane	8:55:02 AM	6
Edward	8:57:35 AM	1
Diane, Martin, & Alice	9:08:02 AM	26
Roseanne	9:08:40 AM	1
Edward	9:15:06 AM	7
Edward	9:18:55 AM	1
Jane	9:21:10 AM	6
Alex	9:25:04 AM	3
Jane	9:34:18 AM	1
Holly	9:38:46 AM	11
Adam	9:47:25 AM	9
Holly	9:52:23 AM	8
Erin	10:09:15 AM	7
Jane	10:11:46 AM	6
Jane	10:18:35 AM	5
Diane	10:20:30 AM	1
Jane	10:42:38 AM	11
Jane	10:48:33 AM	2
Jane	10:54:32 AM	2
Laura	11:05:47 AM	2
Adam	11:12:24 AM	12
Jane	11:13:37 AM	1
Hector	11:15:37 AM	3
Hector	11:45:44 AM	3
Erin	12:09:06 PM	1
Erin	12:12:08 PM	1
Hector	12:17:41 PM	17
Hector	12:22:14 PM	8
Hector	12:25:47 PM	4
Hector	12:33:12 PM	3
Hector	12:42:20 PM	3
Hector & Erin	12:47:47 PM	4
Hector	12:51:11 PM	4
Erin	1:06:31 PM	2
Erin	1:20:03 PM	1
Lara	1:20:08 PM	6
Erin	1:22:51 PM	1
Erin	1:58:40 PM	7
Hector	1:59:34 PM	5
Hector	2:10:10 PM	7
Erin	2:17:31 PM	5
Erin	2:29:09 PM	1
Hector	2:37:34 PM	18
Laura	4:17:17 PM	18

* Note that while Tom has many short interactions, the majority of those interactions do not provide much new exposure to others. This is because Tom's interaction partners are not themselves meeting with many other people in between their meetings with Tom.

As a result, while Tom and Martin interact the same amount – and they interact with the same number of people – the exposure they obtain as a result of their interactions is very different. Martin achieves exposure to a wide variety of people throughout the day, because his interaction partners are not very redundant. By contrast, Tom spends much of his time engaging in interaction with a set of people who form an inner circle, repeatedly interacting with each other. Thus, Tom has low interaction efficiency – given the amount of time he spends interacting, he receives fairly low updates (exposure to others) through his interactions. Martin has high interaction efficiency, since given the amount of time he spends interacting, he acquires a high amount of updates.

Controls

Controls include gender, management position, and tenure. In addition, Casciaro, Carley and Krackhardt (1982) found that people with higher positive affect were less accurate in reporting their advice ties, demonstrating that personality plays a role in network perception accuracy. In this study, I wish to control for the influence of personality, and so include extraversion, which has been strongly linked to positive trait affect (Rusting and Larsen 1997).

RESULTS

First, it is interesting to note the distribution of the dependent variable, relational acumen. On average in the department, people had relational acumen of 0.34. This means that what people perceived as the strength of their relationships with others was not very highly correlated with what other people thought about those relationships. Most people's relational acumen is below 0.6, and no one achieved a level of 0.7 or higher. See Figure 12.

FIGURE 12: DISTRIBUTION OF RELATIONAL ACUMEN

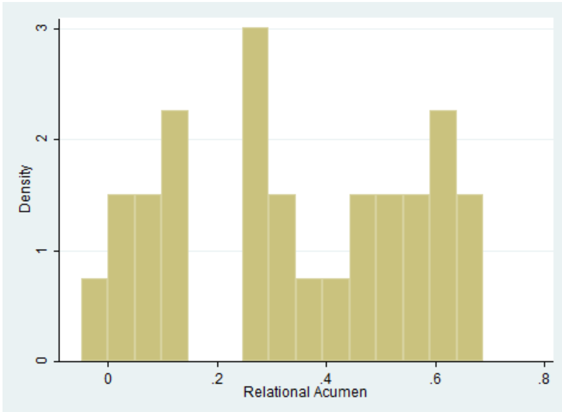
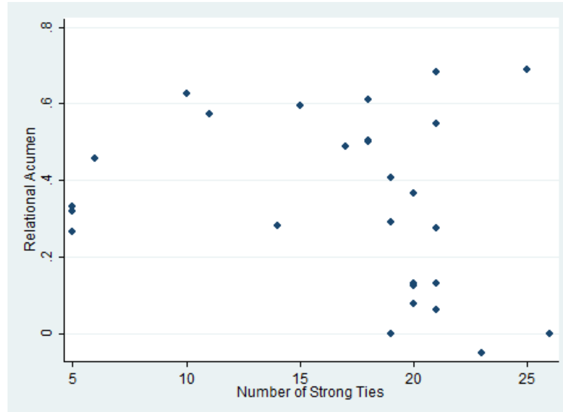


FIGURE 13: RELATIONAL ACUMEN VS. NUMBER OF STRONG TIES



Network measures at Time 1, degree and constraint, are moderately correlated with Time 3 relational acumen. See descriptive statistics and correlations in Table 16. With a correlation of -0.35 for constraint and 0.30 for degree, this indicates that higher centrality and lower constraint is related to higher subsequent relational acumen, as expected. Measures based upon interaction patterns –average updating frequency and interaction efficiency – are also positively correlated with the dependent variable as expected.

Readers may wonder if relational acumen (a Time 3 measure) is driven by the number of strong ties a person has at Time 3. A strong tie exists at Time 3 when two people agree that the relationship they have with each other is strong. By definition then, when a person has strong ties, his or her accuracy about those particular relations is high. However, even when a person has many strong ties, this does not mean that the person's overall relational acumen is high. He or she may (or may not) have been accurate about the other relations, which means that relational acumen can still vary considerably even when a person has a many confirmed strong ties. See Figure 13; the correlation between relational acumen and strong ties is -0.23. A similar pattern results when comparing relational acumen to network degree at Time 3; the correlation between Time 3 relational acumen and Time 3 network degree is 0.05. These results reduce the concern that the correlation between Time 1 degree and Time 3 relational acumen is caused by the mathematical properties of the measures.

TABLE 16: DESCRIPTIVE STATSTICS AND CORRELATIONS FOR VARIABLES

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8
1. Relational Acumen (DV)	0.34	0.23	-0.05	0.69								
2. Male	0.63	0.49	0.00	1.00	-0.20							
3. Manager	0.22	0.42	0.00	1.00	0.15	0.04						
4. Tenure (years)	17.98	6.89	4.75	30.83	-0.31	0.15	-0.12					
5. Contact Network Degree	22.33	6.30	1.00	28.00	0.30	-0.01	0.30	-0.16				
6. Contact Network Constraint	0.19	0.17	0.13	1.00	-0.35	0.10	-0.14	0.01	-0.79			
7. Total Interaction Hours	98.59	40.73	27.25	195.27	0.01	-0.25	0.51	-0.22	0.11	0.04		
8. Average Update Frequency	190.78	59.19	64.00	311.00	0.14	-0.20	0.47	-0.16	0.07	0.03	0.92	
9. Interaction Efficiency	0.24	0.89	-1.71	1.92	0.33	0.10	-0.08	0.13	-0.09	-0.03	-0.15	0.24

Table 17 reports the results of Tobit regression models predicting relational acumen. Since relational acumen is a correlation measure, it can only vary from -1 to 1; these form the upper and lower limits for the dependent variable in the tobit regression. Two controls, gender and extraversion, were tested in multiple models, but were consistently not significant and did not affect results for other variables. They are removed from the analysis reported here. While managerial position is also not significant in models, its absence affects the results of other variables, and so it is kept in the analysis. Surprisingly, tenure is significantly related to decreased relational acumen in some models. Generally, one might expect enhanced relational acumen as tenure increases, due to increased experience in that social environment. However, at this study site, the reverse is true. Perhaps given the high levels of tenure – up to 30 years – this result indicates that those who accumulate extensive experience in the organization can become less attentive to social cues that indicate relationship strength.

TABLE 17: TOBIT REGRESSION MODELS PREDICTING RELATIONAL ACUMEN

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Tenure	-0.010	-0.009	-0.010+	-0.010	-0.011*	-0.011*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Manager	0.060	0.022	0.035	0.047	0.073	0.048
	(0.098)	(0.099)	(0.092)	(0.110)	(0.089)	(0.084)
Network Measures (Time 1)						
Degree		0.009				
		(0.007)				
Constraint			-0.466+			-0.443*
			(0.233)			(0.212)
Interaction Measures (Time 2)						
Average Updating Frequency				0.000		
				(0.001)		
Interaction Efficiency					0.099*	0.095*
					(0.043)	(0.040)
Constant	0.508***	0.299	0.601***	0.470*	0.509***	0.598***
	(0.119)	(0.195)	(0.121)	(0.193)	(0.109)	(0.110)
Observations	27	27	27	27	27	27
Chi-squared	3.165	4.878	6.883	3.225	8.015	12.054
Prob > Chi-squared	0.2054	0.181	0.0757	0.3582	0.0457	0.017

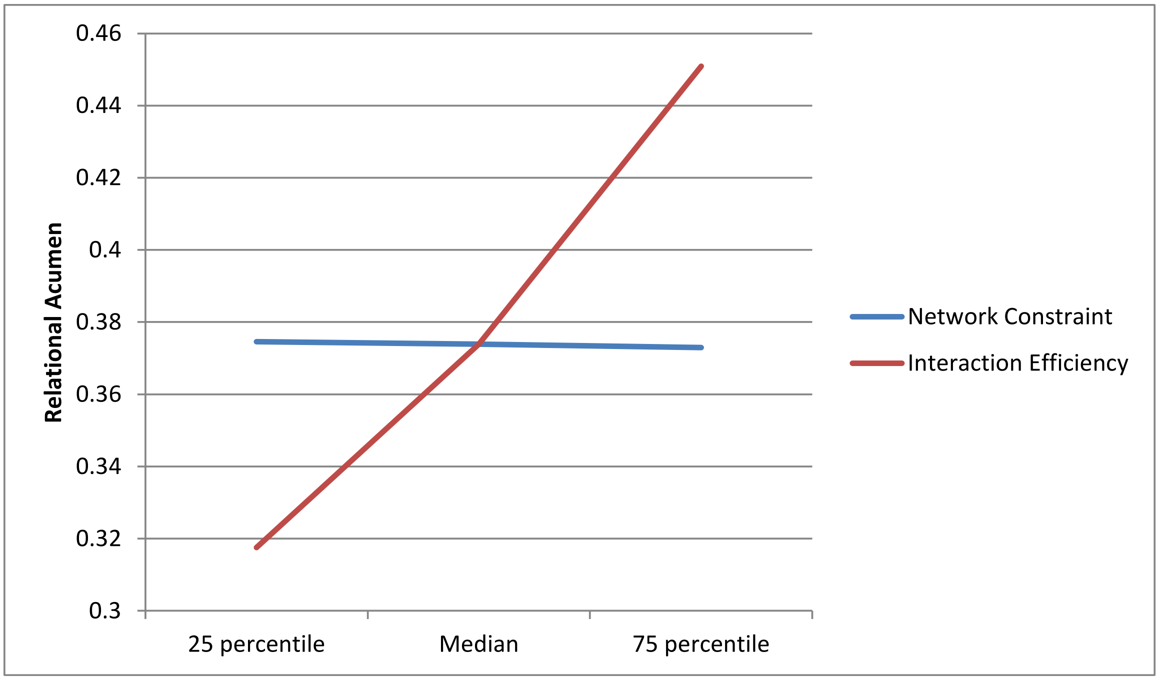
Standard errors are in parentheses. Two-tailed tests for all variables.
+ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

After controlling for managerial position and tenure, degree centrality is not significantly related to relational acumen (Model 2). Hypothesis 1 is not supported. By contrast, network constraint in Model 3 is marginally significantly negatively related to relational acumen, providing support for Hypothesis 2; the more redundant a person's contacts are, the less accurately he or she is able to interpret the strength of his or her relations.

Surprisingly, Model 4 reveals that updating frequency is not significantly related to relational acumen. This means Hypothesis 3 is not supported. However Model 5 shows a significant positive effect of interaction efficiency on relational acumen, providing support for Hypothesis 4. The more efficient one's interactions, in the sense of providing higher levels of exposure to others with less interaction time, the higher one's relational acumen. Since Hypothesis 4 is supported, readers may wonder if the total time a person engaged in interactions (total interaction hours) has an effect on relational acumen. In fact, total interaction hours does not predict relational acumen, either when analyzed alone, with other controls, or in combination with the independent variables (models not reported here).

In the final model, Model 6, both constraint and interaction efficiency are tested together. Each is independently significant, providing further support for Hypothesis 4 and Hypotheses 2. While Table 17's results indicate that both network constraint and interaction efficiency are each independently predictive of relational acumen, they are not equally meaningful in doing so. Figure 14 shows the effects of constraint and information efficiency on predicted values of relational acumen. Each line shows the effect of variation in the variable indicated, holding other variables at their median. Model 6 was used to calculate predicted values. The influence of increasing constraint, from the 25^{th} percentile to the 75^{th} percentile, produces a very small change in relational acumen: -0.0016. It is worth emphasizing that constraint is a significant predictor of relational acumen, and the blue line in Figure 14 decreases slightly (it is not flat). However, while constraint is significant, it is not a very meaningful determinant of relational acumen. On the other hand, an increase from the 25^{th} percentile of interaction efficiency to the 75^{th} percentile of interaction efficiency produces a dramatic 0.133 improvement in relational acumen. In sum, while having redundant contacts matters, it is interaction efficiency which increases or decreases relational acumen the most.

FIGURE 14: EFFECTS OF NETWORK CONSTRAINT AND INTERACTION EFFICIENCY



DISCUSSION

Results provide support for Proposition 2 (Hypotheses 2 and 4) rather than Proposition 1. This means that a person's ability to efficiently access social information is key to determining his or her relational acumen. However, the absolute level of access to social information (Proposition 1, Hypotheses 1 and 3) is not helpful for accurately interpreting the strength of one's relations. Further, results show that while social network position (network constraint) and interaction (interaction efficiency) both contribute toward predicting relational acumen, it is interaction efficiency which is the most meaningful predictor.

In addition to showing that efficient access to social information is important for relational acumen, this study provides several new insights. First, relational acumen was argued in the introduction to be an important factor in a person's ability to effectively utilize his or her network. While it remains for future work to test the relationship between relational acumen and other important outcomes, the results here indicate that people do vary substantially in how accurately they perceive the strength of their relationships. With an average relational acumen of 0.34, which is the correlation between the self's perceptions of relationship strength and others' perceptions of relationship strength, this means that misperceptions are common. The potential for frustration, wasted effort, and missed opportunities as people attempt to use their networks is high. The results at this site are especially interesting because the department has a very stable social environment. Employees have fairly high tenure – on average over 17 years of service at ManuCorp – and so many people have known each other for decades.

Second, the results indicate that how one interacts with others matters: The choices one makes about whom to see when, in what order, and how often, all affect one's access to useful social information. If a person wishes to increase his or her access to social information, then he or she can seek out interactions which are likely to bring higher exposure to others. This emphasizes the role of agency in networks. Relations are enacted through interaction, and interaction patterns often deviate from what would be expected from the structure of the social network. As a result, trying to understand social information flow requires assessing how specific groups enact their relations in day-to-day interactions.

For some people, the idea of "interaction efficiency" may conjure an image of an "efficient" but anti-social worker who shuns relationship building and water cooler talk. He or she keeps interpersonal interactions to a minimum in order to spend the most time working. Therefore, it is important to note that interaction efficiency here does not mean interaction minimization: Participants with both high and low amounts of overall interaction time can have higher interaction efficiency scores; and overall interaction time had no effect on relational acumen. The examples of Martin and Tom illustrate that interaction efficiency has more to do with how wide or narrow one's exposure to others is through interactions, instead of how many interactions one has. So the implication is not that those with higher interaction efficiency have minimal interaction – rather, they have reduced interaction time relative to the amount of exposure they acquired through those interactions. This enables their interactions to be more effective, encouraging the transmission of more valuable social information. In fact, water cooler talk can be quite efficient, when it brings together people from different parts of the department, who can provide novel information to each other in a brief period of time. When a water cooler gathering involves people who already see each other often during the day, however, this is much less efficient.

Interaction efficiency is similar to the idea of network brokerage, the lack of network constraint. Network brokers are expected to receive higher levels of novel information because of their access to non-redundant alters, in the same way that interaction efficiency provides higher exposure to others. In other words, network brokers should have higher interaction efficiency. Yet, the correlation between constraint and interaction efficiency at this site is extremely low (-0.03). These results indicate that people who are brokers may or may not enact their networks to obtain the brokerage value that they potentially have access to. And people with higher constraint can use their networks in a way that actually increases the novel information they receive.

Finally, this paper utilized a novel method of analyzing interaction data, based on the sequence of interactions that occurred over a course of nine weeks at ManuCorp. The interaction analysis method emphasizes tracing flows (exposure to others) through interactions, rather than assessing the structure created by relationships. With this approach, researchers can analyze the flow of information in other contexts and using other forms of physical and virtual interaction data, such as email data and cell phone data. The method may also be modified to introduce more realistic assumptions about information transmission. For example, old interactions may be forgotten after a period of time (information decay rates) and not all recent information may be conveyed at each interaction (varying triggers for transmission).

CONCLUSION

In summary, this paper highlights that people's judgments about their relationships vary in their accuracy. When people misjudge their connections, this can result in frustration, wasted effort, and missed opportunities as they seek to obtain help from others. Relational acumen, the ability to accurately perceive the strength of one's relations, is thus a key ingredient for obtaining network benefits such as access to resources and support. Yet relational acumen is not simply an individual skill or personality trait. It is the product of a social process. As people within a social context communicate and share information with each other, they provide meaning and interpretation for each other's behaviors and relationships. Results at ManuCorp demonstrate that these social information flows are what enable people to more accurately interpret their social connections. Higher relational acumen is achieved by those whose day-to-day interactions efficiently increase their access to novel social information.

This study's findings highlight the importance of studying the day-to-day interactions of people within organizations and contribute to the growing literature on network activation (e.g. Smith, Menon, and Thompson 2012; Smith 2005). The network activation literature has shown that people often cannot take full advantage of the benefits that their networks should in theory provide. For example, when people need help or information, they only seek it from a subset of contacts, ignoring other contacts which could be helpful (Smith, Menon, and Thompson 2012). This means that in order to better understand how and why people obtain network advantage, we must assess not only the structure of relations, but also how those relations are activated by people when they need network resources. Two individuals who occupy a similar structural position within a network may have very different actual access to social information as a result of their day-to-day interaction patterns, leading them to have varying accuracy in their judgments about their relationships and whom to consult when the need arises.

Chapter VI: Conclusion

Putting it Together: Relational Schemas, Interaction Efficiency, Network Position, and Relational Acumen

The three papers in this dissertation have in common the goal of illuminating the specific social mechanisms that produce access to information and/or relational knowledge. In Paper 1, social experience (tenure in the organization) and social position (network contacts) were found to influence the development of relational schemas, a form of relational knowledge. Further, the variety of relational schemas was found to increase a person's relational acumen, the ability to accurately judge the strength of his or her relationships. Paper 2 demonstrates that network position (specifically degree and closeness) influences a person's interaction patterns, providing the mechanism for access to information. And Paper 3 finds that both network position (brokerage/constraint) and interaction patterns which provide higher access to information holding constant interaction time (interaction efficiency) improve relational acumen, although the strongest effect is produced by interaction patterns.

How can this collection of findings be made sense of as a whole? First, both Paper 1 and Paper 3 have in common one dependent variable: Relational Acumen. Yet the mechanisms which they employ to explain relational acumen are different. On the one hand, Paper 3 makes an argument based on exposure to information – the more efficiently one is exposed to information, the greater one's ability to interpret that information, which translates to more accurate perceptions. On the other hand, Paper 1 employs an argument based on information processing. The more varied one's relational schemas, the better one can attend to and interpret diverse information about others in order to have more accurate perceptions.

These mechanisms are very compatible, and in fact, each presumes the operation of the other. For exposure to information to produce greater understanding, one must have the cognitive capacity to interpret the higher level of information one receives. Similarly, for information processing capability (variety of relational schemas) to produce greater understanding, one must actually encounter/receive information to process. As a result, we should expect that a person who has developed a high variety of relational schemas through years of experience in an organization, but who is socially isolated on a day-to-day basis, would not have high relational acumen because he or she has lost touch with the ever-evolving social environment. And a person who has high interaction efficiency but also cognitively lumps relations to a high degree also could not have high relational acumen, because much of the information he or she is exposed to that is not relevant to his or her narrow set of schemas will not be attended to. This logic suggests an interaction effect between the variety of relational schemas and interaction efficiency. A person who has both high interaction efficiency and greater variety of relational schemas has both the opportunity and cognitive tools to become more accurate in assessing his or her social environment.

It remains for future work to test this expectation that variety of relational schemas and interaction efficiency each amplify the effect of the other on relational acumen. Until then, a more general insight is that the combination of results from Paper 1, Paper 2, and Paper 3 suggest that there are up to three pathways through which network position affects relational acumen. First, network position affects relational schema development, which in turn affects relational acumen. Second, network position affects daily interaction patterns, through the choice of interaction partners (Paper 2), and interaction patterns affect relational acumen. Finally, network position itself directly influences relational acumen. Given the low number of observations in this study, it is not possible to tease out the precise relationship between these pathways, since moderation or mediation analysis would require more statistical power. However, by highlighting these new pathways, this dissertation brings focus to the ways in which the benefits of networks are contingent on cognitive and behavioral processes. In this case, network position alone does not provide a comprehensive explanation for who develops a more accurate understanding of their social environment. Instead, network position should be understood to trigger both cognitive and behavioral processes which in turn produce advantage for some actors and not others.

As noted in each of the papers, a main limitation of these studies is the small sample size at ManuCorp. Therefore, the results found should be understood as suggestive. While the approach taken in the papers involves hypothesis testing, the overarching goal here is more exploratory, in the sense of providing a roadmap for future research to more concretely study the interconnections between cognition, daily interactions with others, network position, and outcomes of interest. Thus, the strength of this dissertation is that the data at ManuCorp permitted this comprehensive – though not robust – analysis. There are few studies which combine such a variety of data collection methods to permit analysis of cognitive, behavioral, and structural factors at the same time. Hopefully the insights gleaned from ManuCorp will promote further studies which undertake similarly comprehensive and cross-disciplinary goals.

Overall Contributions

This dissertation integrates cognitive, behavioral, and structural factors in interpersonal dynamics, crossing the disciplines of sociology, psychology, and organizational studies. Considered broadly, the three studies in this dissertation emphasize that the study of social networks should take into account a) cognition and b) action when explaining network outcomes. The wealth of prior research in social networks has shown that the relationships that people have – their network contacts – are important resources for success. However, we know little about how well people actually activate their networks. One of the implications of Paper 3 is that in fact some people, those who have low relational acumen, which is one form of network cognition, will struggle to obtain the network benefits they have access to. Although their networks might be abundant in resources, such as opportunities for help, information, and support, having low relational acumen means they are less able to identify which contacts to approach when different needs arise. People's cognitions about their networks, such as their judgments about whom to go to for resources, are an important source of variation in network benefits that has yet to be explored by social network research. We know that those who have more accurate perceptions about network structure are seen as having more power in organizations (Krackhardt 1990), but the link between network cognition and successful network activation has yet to be investigated.

Yet cognition about network relationships is also affected by network structure. As Paper 1 shows, centrality in a social network affects how many relational schemas and scripts a person comes to hold. That is, a person's understanding of how to interact with others on a day-to-day basis is influenced by the amount of exposure he or she has to others. Thus, the relationship between cognition, social structure, and performance is complex: How people think about their relationships influences the advantage they acquire from those relationships, but their positions in networks also influence how they think about their relations. Further study of cognition in networks must take into account ways in which cognition both influences and is influenced by structure.

Moreover, the role of action sequences – patterns of individual communication behavior – should be studied more in social network research. While a person's network contacts provide potential network resources, it is the person's actual choices of whom to communicate with and when that provide access to those resources. As Paper 2 suggests, activated network benefits, such as access to information and timeliness of information, are related to network position. The more contacts a person has, the more people that person will interact with on a day-to-day basis. However, how much information a person is exposed to over time can vary considerably from the number of contacts the person has, due to the daily choices people make and the temporal ordering of events.

In sum, this dissertation suggests that in order to better understand how and why people obtain network advantage, we must assess not only the structure of relations, but also how people come to understand their relationships, how these cognitions translate into action in interacting with relational partners, and how the pattern of interactions provides access to network benefits.

Appendices

APPENDIX 1: INTERVIEW PERSONALITY QUESTIONNAIRE

Disagree strongly	Disagree moderately	Disagree a little	Neither agree nor disagree	Agree a little	Agree moderately	Agree strongly
1	2	3	4	5	6	7

I see myself as:

_______ Extraverted, enthusiastic.

_______ Critical, quarrelsome.

_______ Dependable, self-disciplined.

_______ Anxious, easily upset.

_______ Open to new experiences, complex.

_______ Reserved, quiet.

_______ Sympathetic, warm.

_______ Disorganized, careless.

_______ Calm, emotionally stable.

_______ Conventional, uncreative.

APPENDIX 2: CALCULATING INFORMATION FLOW MEASURES

To calculate these measures, first the time-ordered interaction data must be processed to create the knowledge matrix and an update log which records each update of information a person receives (Figure 2-Figure 5, earlier). The following describes in plain language the algorithm which I implement to achieve this.

1. Generate empty knowledge structure, an N x N matrix, where N is the number of people in the dataset
2. Generate an empty table which will log the updates that occur. The fields of this table are Person 1, Person 2, Interaction Time, and Information Time.
3. Process each interaction from earliest to latest, in time order. For each interaction between A and B at time T:
    a. Set the value of the knowledge matrix cells (A, B) and (B, A) = T
    b. Create a new row in the updates log, with the values (A, B, T, T)
    c. Create a new row in the updates log, with the values (B, A, T, T)
    d. Compare the non-A& B columns of rows A and B of the knowledge matrix. For each column C:
        i. If the time t_x in cell (A,C) is later than the time in cell (B,C), then:
            1. Set the value in the knowledge matrix in cell (B, C) = t_x
            2. Create a new row in the updates log, with the values (B, C, T, t_x)
        ii. If the time t_x in cell (B, C) is later than the time in cell (A, C):
            1. Set the value in the knowledge matrix in cell (A,C) = t_x
            2. Create a new row in the updates log, with the values (A, C, T, t_x)

After processing all of the interactions, the Updating Frequency (directional dyadic measure) for each person A with respect to each other person B is calculated as the number of rows in the update log where Person 1 = A and Person 2 = B. The individual level Average Updating Frequency and Standard Deviation of Updating Frequency is calculated as the average and standard deviation of the dyadic Updating Frequencies. The Age of Information (directional dyadic measure) for each person A with respect to each other person B is calculated as the average of (Information Time – Interaction Time) over all rows in the update log where Person 1 = A and Person 2 = B. The individual level Average Age of Information and Standard Deviation of Age of Information are calculated based on those dyadic results.

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