ESSAYS ON VISUAL REPRESENTATION TECHNOLOGY AND DECISION MAKING IN TEAMS

A Thesis
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
College of Management

Georgia Institute of Technology
August 2012

ESSAYS ON VISUAL REPRESENTATION TECHNOLOGY AND DECISION MAKING IN TEAMS

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To my family and friends

ACKNOWLEDGEMENTS

Looking back on my life at Georgia Tech, I receive enormous support from many people. Without their support, I cannot have this fantastic achievement. I would like to express my gratitude to those who have been an essential part of my achievement.

First of all, I am especially grateful to Sandy Slaughter, my advisor. I want to thank her for guiding me when I am struggling and encouraging me when I am frustrated. In addition, she serves as my role model in research and teaching.

Second, I would like to thank my committee members: Ruth Kanfer, Jason Kuang, Eric Overby, and Ben Herndon. They generously provide me with constructive feedbacks. I also want thank the other IT faculty members, Sir Narasimhan, Saby Mitra, Han Zhang, D.J. Wu, Chris Forman, Florin Niculescu, and Lizhen Xu, for their advices.

My journey would not have been wonderful without my friends at Georgia Tech. My sincere appreciation goes to Denny Yin, Ongard Singtokul, Shanti Anak Agung, Lin Jiang, and Amy Wen. The moments we shared together are extremely important in my memory. Next, I would like to thank my student cohort of Sam Ransbotham, Jewel Qu, Jifeng Luo, Tiger Song, Peng Huang, Wen Wen, Bin Li, German Retana, Tianshi Wu, Mike Frutiger, Hemang Subramanian, Tina Xu, Sarah Liu, and Stephan Hi for their friendship.

Lastly, my utmost gratitude goes to my parents, Jung-Tsung Peng and Pao-Kuei Liu for their unconditional love and persistent support. I would also like to thank the other family members, Maggie Peng and Gisele Ouyang, for their invaluable encouragement.

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SUMMARY

Information technology has played several important roles in group decision making, such as communication support and decision support. Little is known about how information technology can be used to persuade members of a group to reach a consensus. In this dissertation, I aim to address the issues that are related to the role of visual representation technology (VRT) for persuasion in a forecasting context. VRTs are not traditional graphical representation technologies. VRTs can select, transform, and present data in a rich visual format that facilitates exploration, comprehension, and sense-making. The first study investigates conditions under which teams are likely to increase the use of VRTs and how the use of VRTs affects teams' consensus development and decision performance. The second study evaluates the effects of influence types and information technology on a choice shift. A choice shift is the tendency of group members to shift their initial positions to a more extreme direction following discussion. A choice shift is also called group polarization. To complement my first two studies, I conduct a laboratory experiment in my third study. I explore the effect of VRTs and team composition on a choice shift in group confidence.

CHAPTER 1

OVERVIEW

The benefits of teams can be even more evident when teams utilize appropriate information technologies to support decision making. Teams are very popular at all levels of organizations, such as top management teams, R&D teams, and customer service teams. One of critical reasons of using teams, rather than individuals, is to bring multiple perspectives to make important and consequential decisions. To effectively make decisions, team members can use a variety of information technologies to support their decision making. Based on the goals of decisions, specific communication media/technologies (e.g., face-to-face, video-conferencing, Internet Chat, and email) can be selected by team members to facilitate their communication. For instance, face-to-face teams are likely to reach a higher level of consensus than are virtual teams, but virtual teams are likely to produce more unique ideas than are face-to-face teams (George et al. 1990; Valacich et al. 1994). Virtual teams are compute-mediated communication teams. Although face-to-face teams are still the most popular, organizations are increasingly using virtual teams because of low-cost communication technologies. Recent studies conducted by *Gartner Group* and *The Economist* indicate that 41 million corporate employees worldwide perform tasks virtually one day per week (Jones 2005) and nearly 78% of employees have worked in a virtual team (Witchalls 2009).

In addition to communication technologies, team members can also use information technologies to support their decisions. Characteristics of information technologies have different effects on the facilitation of information processing and decision making. Some studies have focused on the representations of information technology and have found that graphic representation technologies reduced time for information processing and decision making more than did text/non-visual representation technologies (Benbasat and Dexter 1985; Benbasat and Dexter 1986; Jarvenpaa 1989). Moreover, the level of interactivity is an important technology characteristic. Prior studies have demonstrated that interactivity can facilitate information processing, reduce decision effect, and enhance decision performance (Jiang and Benbasat 2007; Tan et al. 2010; Wang and Benbasat 2009).

We already know information technology can be used to support communication and information processing. However, there is relatively little research about how team members use information technologies to persuade other members and reconcile their differences (Fogg 2003). This is an important question because technology designers, team leaders, and researchers all want to know how to leverage the power of information technology. Overall, the objective of this thesis is to investigate how decision-making teams draw upon information technologies for persuasion. Specifically, I focus on visual representation technologies (VRTs).

VRTs are not traditional graphical representation technologies. VRTs can select, transform, and present data in a rich visual format that facilitates exploration, comprehension, and sense-making (Card et al. 1999; Lurie and Mason 2007). SmartMoney technology of the Wall Street Journal (http://www.smartmoney.com/map-of-the-market/) is one type of VRTs. The most salient difference between VRTs and traditional graphical representation technologies is the level of interactivity. Due to recent advances in technical visualization, VRTs include several interactive features which may not be included in traditional graphical representation technologies (Yi et al. 2007a), such as filtering, zooming, and reordering data. Interactive features are able to help decision makers recognize information patterns more quickly, thereby increasing their productivity. In addition to productivity improvement, VRTs may enable decision makers to uncover new insights in the data that may not be easily found using non-visual tools. The following three essays describe my thesis into more detail.

1.1 Essay 1

Essay 1 investigates when virtual teams increase their use of VRTs. Although teams can bring multiple perspectives to bear on important decisions (Hackman and Morris 1975), these perspectives are very likely to lead to very different opinions, low team consensus. Past research has suggested that invoking visual image is likely to reach consensus through immersion into the narrative world (Green and Brock 2002). Therefore, I hypothesize that virtual teams will be more likely to draw on VRTs when initial team consensus is low. In addition, teams need to be confident in their decisions when facing environmental exactingness, the consequences of making judgment errors (Hogarth et al. 1991). Past studies proposed that the use of imagery enhances the ease or fluency with which information is processed which, in turn, increases the perceived persuasiveness of this information and subjective estimates that the information is true (Lee 2004). In other words, the greater accessibility of imagery information increases belief confidence. Thus, I hypothesize that environmental exactingness is positively relate to the use of VRTs. Furthermore, it is reasonable to argue that the use of these technologies is even greater when both conditions are true.

Essay 1 also examines the relationship between use of VRTs and team performance. The use of imagery is very likely to increase confidence of making an accurate decision. The confidence should be related to team performance. I hypothesize that greater use of VRTs is positively associated with team performance.

To test these hypotheses, I conducted a filed study. The research setting is a ten-person virtual team responsible for forecasting air quality for the Atlanta region. From the forecasting website used by the team, I extracted: (1) initial individual forecasts of the next day's ozone concentration, (2) the team's final consensus forecast, and (3) the amount of visual representation technologies used. This study provides evidence that the team's use of visual representation technologies depends on the exactingness of the decision context and the extent to which team members are in agreement. In particular, the team increases its use of technologies for visual representation, such as maps, satellite, and radar imagery, when initial team consensus is low and when facing exacting environments in which the consequences of judgment errors are large. In addition, the study shows that the team reduces its decision bias when the team members use more visual representation technologies during discussion.

This study makes a number of theoretical and managerial contributions. Previous studies have demonstrated that information technologies can be used to satisfy individuals' needs for communication support and decision support. The study contributes to the research on the use of technology for persuasion. I investigate how team members utilize information technology to develop group consensus and facilitate decision making. Because the study focuses on the use of VRT, the study can also add to prior work focused on simple graphic representation technology and non-visual representation technology. The findings of the study suggest that team leaders and members are able to reach a higher level of consensus by considering the portfolio of use of information technologies. Specifically, team members can facilitate the development of consensus when using more visual representation technologies.

1.2 Essay 2

Essay 1 sheds light on the importance of group discussion. During their discussion, group members may use different tactics to persuade other members and then reach group consensus. In Essay 2, I further explore group discussion. Specifically, I examine the effects of influence and information technology on group polarization. Group polarization is the tendency of group members to shift their initial positions to a more extreme direction following discussion. Group polarization is also called choice shift. For example, jurors who initially favor a harsh penalty will make a harsher sentence after discussion, while jurors who initially favor a lower award will agree with a more lenient sentence after discussion.

Group polarization can be explained by two group processes (Sia et al. 2002). The first process is informational influence. Group polarization happens when group members are exposed to persuasive arguments during discussion. The second process is normative influence. Group members are motivated to present themselves in a socially favorable light. Some studies have suggested informational influence as a sufficient and necessary group process, whereas other studies have focused on normative influence (Isenberg 1986). Relatively few studies have explored these two influences simultaneously.

Past research has found that the effect of informational influence on group polarization is larger than that of normative influence (Isenberg 1986). The finding implies that the exposure of informational influence is more likely to change group members' positions than the exposure of normative influence. A high level of the relative use of informational influence versus normative influence indicates that group members are exposed to relatively more informational influence than normative influence. Thus, I hypothesize that the relative use of informational influence versus normative influence is positively associated with the magnitude of group polarization.

Moreover, the effect of the relative use of informational influence versus normative influence on the magnitude of group polarization should be amplified by technology reference. Group members are more likely to shift their initial positions when they are exposed to persuasive information. Persuasiveness of information can be increased by using references or labels (Tseng and Fogg 1999). For instance, people are more likely to believe information from credible source (e.g., Consumer Reports) than information without citing any source. Hence, I postulate that the relative use of informational influence versus normative influence and the intensity of technology reference interact positively in their effect on the magnitude of group polarization.

Furthermore, I explore the relationship between antecedents and the relative use of informational influence versus normative influence. My study investigates two important antecedents, heterogeneity of pre-discussion individual decisions and task uncertainty, since these two antecedents are relevant to consensus development in virtual team settings. A higher level of heterogeneity indicates that a range of group members' opinions is wider. To effectively reconcile differences among them, group members have to share more individual preferences, relative to factual information. Thus, I hypothesize that a level of heterogeneity is negatively associated with the relative use of informational influence versus normative influence. In contrast, a high level of task uncertainty refers to a large gap between the amount of information required to perform a task and the amount of information performers have. To fill a gap, group members need to exchange more factual information and data, relative to individual preferences. Therefore, I posit that a level of task uncertainty is positively associated with the relative use of informational influence versus normative influence.

A field study is used to investigate group polarization, its processes, its antecedents, and information technology. The research setting is a ten-person virtual team responsible for forecasting air quality for the Atlanta region. I find the heterogeneity of pre-discussion individual decisions and greater task uncertainty increase group polarization through a greater relative use of informational influence. Moreover, surprisingly, I find that the relative use of informational influence and the use of information technology for persuasion are substitutive not complementary in their effects on group polarization.

This study makes two important contributions. First, little is known about how the relative use of informational influence versus normative influence is affected by antecedents and affects the magnitude of group polarization in virtual team settings, so the study extends the literature on group polarization by hypothesizing and testing an input-process-output framework. Second, the study contributes to group polarization research and IS research by theorizing the persuasive role of information technology as a credible source of information.

The findings of the study are useful for practitioners. As for an increase in benign group polarization (e.g., making more donations to a community that was hit by a natural disaster), the study suggests that decision makers can encourage their group members to use more informational influence relative to normative influence during group discussion. As for prohibition of hurtful group polarization (e.g., keep investing in the failing Enron Corporation), my suggestion is to use less informational influence relative to normative influence. In addition, decision makers who want to increase the magnitude of group polarization even more should use fewer information technologies when the relative use of informational influence versus normative influence is already high.

1.3 Essay 3

This essay complements the first two essays. Essay 1 demonstrates that team members can utilize VRTs to reach a consensus during discussion and Essay 2 shows that the nature of group discussion affects the magnitude of a choice shift (i.e., one type of group decision outcomes). Prior studies have found that technology usage (e.g., Zigurs and Buckland 1998) and team composition (e.g., Kayworth and Leidner 2000) affect group decision making. However, there is relatively little knowledge of how the use of VRTs and the level of domain knowledge together affect group decision making.

VRTs vary in the level of interactivity, one of the most important characteristics. A technology with a high level of interactivity allows members of a group to interact with a vast amount of data and extract useful insights more easily (Lurie and Mason 2007). Therefore, I hypothesize that groups using a technology with a high level of interactivity increase their confidence following discussion more than do groups using a technology with a low level of interactivity.

In addition, the effect of VRTs on group confidence should depend on the level of domain knowledge. When making decisions, groups with a high level of domain knowledge (i.e., expert groups) have a greater ability to identify relevant information, recognize information patterns, and increase the amount of information considered than do groups with a low level of domain knowledge (i.e., less expert/novice groups). Hence, I hypothesize that groups using a technology with a high level of interactivity increase their decision confidence even more when the level of domain knowledge is high.

To test these hypotheses, I conducted a laboratory experiment in which I manipulated the level of interactivity in technologies (high interactive vs. low interactive) in two different levels of domain knowledge groups (high domain knowledge vs. low domain knowledge). I selected a football forecasting task which has been used in numerous laboratory studies (Sanna and Schwarz 2003; Simmons et al. 2011; Tsai et al. 2008). The results demonstrate that groups increase their decision confidence more by using a high interactive technology than by using a low interactive technology. Moreover, the results show that expert groups using a high interactive technology increase their confidence of predicting an accurate outcome more than do expert groups using a low interactive technology. However, the results do not show that novice groups using a high interactive technology increase their confidence of predicting an accurate outcome more than do novice groups using a low interactive technology.

This study makes two important contributions. Previous studies have focused on the technology interactivity at the individual level (Häubl and Trifts 2000; Jiang and

Benbasat 2007; Tan et al. 2010; Wang and Benbasat 2009). Therefore, the study extends the literature by hypothesizing and testing the effects of technology interactivity at the group level. Moreover, the study contributes to the literature on information system usage by hypothesizing and testing the moderating effect of domain knowledge. The findings of the study are beneficial for practitioners. Predicting a future outcome is complex and difficult, so decision confidence is the first and most important thing. Group decision leaders need to know how to increase group decision confidence, especially, in a forecasting task. The study suggests that groups can increase their decision confidence almost twice as much by using a high interactive technology than by using a low interactive technology. Moreover, expert groups can increase their group confidence four times more by using a high interactive technology than by using a low interactive technology.

CHAPTER 2

VISUAL REPRESENTATION TECHNOLOGIES, VIRTUAL TEAMS, AND CONSENSUS SEEKING IN EXACTING ENVIRONMENTS

2.1. Introduction

Organizations are increasing their use of virtual teams to bring diverse individuals and groups together at lower cost. Although we are learning more and more about technologies that help virtual teams communicate (Yoo and Alavi 2001), and distill large amounts of information to take or recommend actions (Todd and Benbasat 1999), little is known about the persuasive role of information technologies in virtual team settings; in particular, how different technologies may help virtual team members reach consensus.

Persuasion is important in virtual team settings because bringing together people from diverse backgrounds increases the likelihood they will disagree while the lack of physical co-presence makes the resolution of differences more challenging (Martins et al. 2004; Powell et al. 2004). In addition, many virtual teams must make decisions under time constraints and make important decisions for which the consequences for errors are large. The need to reach consensus under time constraints, and the consequences of making errors, means that team members must not only articulate opinions but actively persuade others of the validity of these opinions and increase team confidence in their decisions.

One common approach for successful persuasion is to create an image in the receiver's mind (Petrova and Cialdini 2008). Recent research on persuasion (Chaiken and

Trope 1999; Kahneman and Frederick 2005; Sloman 1996) shows that imagery, and references to images, enhance persuasion through three primary mechanisms: The first involves transportation (Green and Brock 2000), in which imagery processing transports receivers into a different reality in which they are less likely to engage in systematic evaluations of positive and negative features and more likely to holistically accept arguments (Boles 1991). The second involves accessibility, in which the use of imagery enhances the ease or fluency with which information is processed which, in turn, increases the perceived persuasiveness of this information and subjective estimates that the information is true (Lee 2004; Lee and Labroo 2004; Schwarz 2004; Sherman et al. 1985). In other words, the greater accessibility of imagery information increases belief confidence (Tormala et al. 2002). The third mechanism is the connection between imagination and vision, in which imagining objects or pictures activates similar regions of the brain as viewing these objects or pictures (Kosslyn et al. 1999; O'Craven and Kanwisher 2000). This suggests that referring to an image engages the same mechanisms as showing the image.

We propose that the use of information technologies that present information in visual and interactive formats, will engage the imagery processing mechanisms described above thereby enhancing persuasion in virtual teams. In this paper, we are interested in how information technologies are used for persuasion. Thus, by "*use*" we mean *the showing or referencing of a particular information technology, or type of technology, in team discussions*. In particular, we are interested in a class of technologies called visual representation technologies which select, transform, and present data in a rich visual format that facilitates exploration, comprehension, and sense-making (Card et al. 1999;

Thomas and Cook 2005). Specifically, we argue that, in contexts in which persuasion and confidence in decisions are important, virtual team members will increase their use of visual representation technologies. We identify lack of initial consensus and environmental exactingness as contextual factors affecting virtual teams' relative need to persuade other team members and enhance belief confidence. Because imagery processing enhances persuasion as well as belief confidence (Petrova and Cialdini 2008) we hypothesize that virtual teams will be more likely to use visual representation technologies in their discussions when initial team consensus is low, or when the consequences of making errors are high, and that use of these technologies will be even greater when both conditions are true.

We test our hypotheses using a novel data set of the daily technology discussion and decisions of a virtual team making smog forecasts with large economic and health consequences. In particular, we examine use of visual representation technologies and daily ozone level forecasts during the smog season over a three year period by a virtual team responsible for the 5-million person Atlanta region in the United States. This natural research setting provides a rich context for examining technology use by an expert virtual team in which team membership and task are relatively constant but the decision context varies. The setting also affords precise and objective measures of team performance. We observe the team's daily preliminary and consensus forecasts during the summer smog season, the information technologies used in their online chats, and the actual ozone levels recorded on the forecasted days.

By studying the behavior of an expert team engaged in a repeated task we add to studies of novice decision makers in one-shot scenarios with relatively sparse amounts of information (Martins et al. 2004; Powell et al. 2004). While this research has yielded many important insights, the scenarios examined may not adequately reflect decision making as practiced in the real world, in which expert teams interact repeatedly over time to make multiple decisions with real consequences in information-rich and constantly changing environments (Hastie 2001; Klein et al. 1995). Finally, although researchers have long been interested in differences between information presented in graphical versus text format (Benbasat and Dexter 1985; Jarvenpaa 1989), most of this research examines individuals rather than teams and has not examined the persuasive role of information technologies. In sum, studying how an experienced virtual team makes high-consequence decisions in a dynamic and information-rich environment in the same task over time offers a strong test of the extent to which variations in the decision context affect team use of particular types of information technologies.

In sum, our study contributes to the literature on the role of information technology in virtual teams by (a) articulating a persuasive and confidence enhancing role in virtual teams for technologies not specifically designed for communication, (b) theoretically and empirically distinguishing between visual and non-visual technologies in team consensus seeking, (c) identifying contextual (i.e., non-task) factors that affect the role of technology in virtual team settings, and (d) examining the behavior of an expert team that interacts repeatedly over time making decisions with real consequences. Additionally, (e) our use of behavioral data avoids the assumption that respondents have adequate and accurate awareness of their technology use. It also avoids the demand effects, retrospective reporting, and other biases associated with self-reported perceptual data.

In the next sections we develop our hypotheses about how initial team consensus, the exactingness of the decision context, and their interaction should affect a virtual team's use of visual representation technologies. We then describe our research setting, method, and results. We conclude by discussing our results and their implications.

2.2. Imagery Processing and Persuasion

Recent research suggests that imagery processing is particularly important to persuasion in group as well as individual contexts. Imagery is often used by advertisers who urge consumers to "imagine themselves" on a vacation beach, driving a particular vehicle, or winning the lottery. Other research suggests that images can help resolve conflict in organizational settings (Von Glinow et al. 2004). Imagery increases perceptions that an event will occur and increase intentions to engage in a behavior (Petrova and Cialdini 2008). For example, imagining winning a lottery increases beliefs that one will win (Gregory et al. 1982) and imagining blood donation increases intent to donate (Anderson 1983). Imagery processing is enhanced through vividness, such as making images more concrete by showing pictures, and numerous studies have shown that the presence of pictures enhances imagery processing (see Petrova and Cialdini 2008 for a review). Object interactivity also enhances imagery processing. For example, interacting with the features of a camera in an online setting enhances feelings of transportation into the virtual world and increases purchase intentions (Schlosser 2003). Importantly, visual representation technologies often combine visual images and object interactivity allowing users to simulate and imagine experiences (Card et al. 1999; Schlosser 2003).

As mentioned earlier, imagery affects persuasion in three ways: The first is through increased transportation (Green and Brock 2000; Petrova and Cialdini 2008). The second is by enhancing accessibility (Lee and Labroo 2004; Schwarz 2004; Sherman et al. 1985). The third is by activating regions of the brain overlapping with those involved in viewing pictures or objects (Kosslyn et al. 1999; O'Craven and Kanwisher 2000). We elaborate below.

Transportation. Transportation refers to immersion into the narrative world (Green 2004; Green and Brock 2000; Green and Brock 2002). Unlike traditional approaches to persuasion (e.g., Petty and Cacioppo 1981), persuasion through transportation is not affected by argument strength; rather, the immersive quality of transportation makes information seem real, and therefore more believable (Escalas 2007). Through transportation, receivers are more accepting of arguments and less likely to counter argue (Escalas 2004; Green and Brock 2000). The vividness of visual images increases transportation and persuasion by engaging receivers in the narrative. For example, using narratives in vacation brochures enhances consumer evaluations of vacations, which are further enhanced by including pictures that allow consumers to imagine taking a particular vacation (Adaval and Wyer Jr 1998). Similarly, presenting information about high ozone levels in a narrative form should increase beliefs that ozone levels will be high relative to presenting the same information in non-narrative format. Accompanying the narrative with visual evidence should further enhance persuasion.

Accessibility. Accessibility refers to the subjective ease with which mental representations are created. Accessibility involves the metacognitive experiences of processing information. Information that feels more accessible and easier to process has greater credibility, is evaluated more favorably, and is perceived to be more likely to occur (Lee 2004; Lee and Labroo 2004; Schwarz 2004; Sherman et al. 1985). Vivid visual information enhances accessibility by making it easier for receivers to create mental representations (Petrova and Cialdini 2008). For example, describing or showing moving pictures of a storm system on a map should make it easier to imagine the storm. This should increase estimates of the likelihood that the storm will occur.

Activation. Activation refers to the finding that asking someone to create an image in their mind of an object activates regions of the brain that overlap with those active when the object is actually viewed. For example, asking someone to imagine a particular face creates high levels of activation in the fusiform face area (FFA) consistent with viewing actual faces whereas imagining a particular place activates the parahippocampal place area (PPA) consistent with viewing pictures of that place (O'Craven and Kanwisher 2000). Importantly, whether imagining or viewing images, there is little overlap between regions of the brain that are active for faces versus places (O'Craven and Kanwisher 2000). In other words, there is a strong link between the neurological processes involved with imagining and seeing an image although activation strength is stronger for seen versus imagined images (Kosslyn et al. 1999; O'Craven and Kanwisher 2000). This suggests that referencing a visual image, such as a weather map, in a conversation should have similar—but potentially weaker—effects on persuasion as viewing the map itself.

2.2.1 Persuasive Technologies

Prior research suggests that, in addition to adapting information technologies to meet their needs (DeSanctis and Poole 1994; Majchrzak et al. 2000), teams are themselves affected by technologies (DeSanctis and Gallupe 1987; Kiesler and Sproull 1992). For example group decision support (GDSS) technologies can govern the way virtual teams communicate (DeSanctis and Gallupe 1987). For virtual teams seeking to reach consensus through discussion, use of different technologies should activate different cognitive processes (Vessey 1991). In particular, cognitive fit theory (Vessey 1991) suggests that different representations of information facilitate different types of mental processes. For example, visual representation technologies such as the contour map shown in Figure 2.1 use pictures and object interactivity to convey information to decision makers and allow them to change which information is displayed. This suggests that, relative to technologies that are primarily numeric or textual, use of such technologies should encourage imagery processing and therefore enhance persuasion (Petrova and Cialdini 2008; Schlosser 2003).

Because visual representation technologies are more likely to engage imagery processing, and therefore enhance persuasion (Card et al. 1999; Thomas and Cook 2005), we argue that virtual teams will increase their use of visual representation technology in contexts in which the need to persuade is higher. These contexts include low initial team consensus and exacting situations—where the consequences of wrong decisions increase teams' need to feel confidence in their decisions. In the following sections, we examine these ideas in more detail.

2.2.2 Visual Representation Technologies and Consensus

Virtual teams face a number of challenges due to the distribution of members across time, geography, and organizational boundaries. In particular, reaching consensus may be difficult as team members cannot leverage the richness of face-to-face interactions overcome differences in opinions (Martins et al. 2004; Powell et al. 2004). In such instances, the rich images and visual cues provided by visual representation technologies may be particularly useful to persuade and help reconcile differences among distant team members.

One of the purposes of using teams, rather than individuals, is to bring multiple perspectives to bear on important decisions (Hackman and Morris 1975). Virtual teams further enhance the range of perspectives by bringing together individuals from different organizations and locations (Martins et al. 2004). Virtual teams are less likely to reach consensus than face-to-face teams and research suggests that these difficulties may not be overcome through technologies with greater social presence (Dennis et al. 1988; George et al. 1990; Miranda and Saunders 2003; Montoya-Weiss et al. 2001; Straub and Karahanna 1998). In some cases, different perspectives lead to similar conclusions; in others, differences in the ways in which individuals interpret and combine data can lead to very different predictions, or low initial team consensus (Priem et al. 1995). We expect that virtual teams will increase their use of visual representation technologies when initial team consensus is low.

Invoking visual images is likely to enhance persuasion through immersion into the narrative world and greater acceptance of arguments (Green 2004; Green and Brock 2000; Green and Brock 2002). In other words, use of visual representation technologies should make team members more open to persuasive arguments and enhance consensus seeking. The importance of engaging imagery processing should be more pronounced in virtual settings where it is harder to enhance non-visual information with body language, facial expressions, and tone of voice (Cramton 2001). To the extent that experienced team members (implicitly) understand the consensus seeking benefits of visual representation technologies, they should increase their use of visual representation technologies when initial team consensus is low. Thus,

HYPOTHESIS 1 (H1): *A lower level of initial team consensus leads to greater use of visual representation technologies by team members.*

2.2.3 Visual Representation Technologies and Environmental Exactingness

Although many virtual teams engage in repeated tasks, the environment in which tasks are conducted may vary. One important way in which environments vary is the exactingness, or the consequences of making judgment errors (Hogarth et al. 1991; Hogarth and Karelaia 2007). In our setting—smog forecasting—although the virtual team engages in the same forecasting task each day, environmental exactingness varies from day to day. In particular, the consequences of judgment errors are greatest when the team's initial smog forecasts lie close to a smog alert border. If, for example, the team makes a forecast for ozone levels that is just one part-per-billion below the smog alert level and the team does not issue a smog alert, but the environmental conditions on the following day actually would have warranted a smog alert, citizens of the city may be harmed because they are unaware of unfavorable air conditions. Conversely, the team could decide to agree upon a forecast for ozone levels that is one part-per-billion higher than the initial forecast, and call a smog alert, but environmental conditions on the following day actually may not warrant a smog alert, and citizens could needlessly spend time and money adjusting their work and commuting behaviors. Prior research shows that increased exactingness leads to greater information search (Hogarth and Karelaia 2007). High levels of exactingness (i.e., severe punishment of errors) can even lower performance as decision makers struggle to understand the relationship between independent and dependent variables and distinguish systematic from random effects (Hogarth et al. 1991).

We expect that virtual teams will increase their use of visual representation technologies when environmental exactingness is high. Humans' highly evolved ability to process visual (vs. text) information (Lurie and Mason 2007; Sloman 1996), means that visual information should be easier to process. From a metacognitive standpoint, this greater ease of processing should enhance persuasion and confidence in persuasive messages (Lee 2004; Lee and Labroo 2004; Schwarz 2004; Sherman et al. 1985). In other words, engaging imagery processing by using visual representation technologies will make it easier for recipients to process information. This should then lead to inferences that because the information is easy to understand and process, it is more likely to be true. This, in turn, should increase confidence in decisions based on this information. Greater confidence in information should be particularly important for teams in exacting contexts in which the consequences for error are high. In other words, the greater need by virtual teams to be confident in their decisions in exacting environments should enhance their use of visual representation technologies. Therefore:

HYPOTHESIS 2 (H2): *More exacting environments lead to greater use of visual representation technologies by team members.*

Engaging associative processes should be of even greater benefit when initial team consensus is low and environmental exactingness is high. When initial team consensus is low, an individual must make convincing arguments to persuade other team members to agree with his or her viewpoint. This need to persuade is amplified in exacting environments. Given the severity of consequences for even small mistakes in such environments, the "evidence" or logic of the persuasive argument made by the individual must be even more compelling to convince his or her teammates (Chaiken 1980; Petty and Cacioppo 1986). In such situations, increased processing fluency for imagery information should be even more beneficial.

In our setting, such a situation occurs on days when there is a high variation in the initial individual forecasts for the next day's ozone level and when the average of these individual forecasts is very close to the level at which a smog alert would be issued. If the team agrees upon a forecast that is one part-per-billion below the smog alert border, it will not issue a smog alert. However, if the team decides on a forecast that is one part-per-billion above the smog alert border, it will issue a smog alert for the next day. Thus the exactingness, or consequences of making an error, in this situation are significant. If the team does not issue an alert, but the actual conditions on the next day are unhealthy, members of the public may fail to protect themselves and suffer health consequences; conversely, if the team does issue an alert, and the actual conditions on the next day are not in the unhealthy zone, there may be significant unnecessary economic costs. In this low consensus and high exactingness decision context, individual team members need to convince skeptical teammates with compelling "evidence" for calling (or not calling) a smog alert. For example, an individual forecaster who believes that the ozone level will not warrant a smog alert could use a contour plot technology—that visually illustrates wind velocities, heights, temperatures and wind vectors—to argue that high winds on the next day will clear the air. Given the superior ability of visual representation technologies to engage imagery processes, enhancing transportation and information accessibility, greater use of visual representation technologies should increase persuasion, raise confidence in these persuasive messages, and reduce the likelihood of disputes by other team members. Thus:

HYPOTHESIS 3 (H3): *The effect of lower initial consensus on increasing use of visual representation technologies should increase with environmental exactingness.*

2.2.4 Visual Representation Technologies and Team Performance

We have argued that certain decision contexts (namely, lower initial team consensus and higher environmental exactingness) will invoke increased use of visual representation technologies. However, it is not clear whether use of visual representation technologies is associated with higher team performance. Indeed, prior research finds mixed effects of information technology on team performance (Driskell et al. 2003; Martins et al. 2004). For example, some research has found no difference in the performance of computer-mediated and face-to-face teams (Cappel and Windsor 2000) while other research has found that computer-mediated teams sometimes perform worse (Andres 2002) or better (Schmidt et al. 2001) than face-to-face teams.

In our setting—smog forecasting, bias and accuracy are the primary measures of performance (U.S. Environmental Protection Agency 2003). Bias is the difference between the predicted and observed ozone concentration level. Negative values for bias reflect a tendency to under predict while positive values suggest a tendency to over predict. Accuracy is the absolute value of the difference between the predicted and observed ozone concentration level. More accurate predictions are shown by values closer to zero. Conversely, a higher value for this measure reflects the inaccuracy of the prediction.

Air quality forecasting is a difficult task, and is particularly challenging in the Atlanta area. For example, thunderstorms can unexpectedly develop and clear out air pollutants and accidents can trigger major traffic congestion that increases air pollutants. In addition to being difficult, accurately forecasting air quality levels has significant economic as well as health consequences. When a smog alert is declared, individuals as well as businesses, schools, and other organizations incur substantial costs as they must implement procedures that alter work, school and driving patterns. Smog alerts also have significant health consequences, particularly for individuals with respiratory problems who should stay indoors when ozone levels are high. These large economic and public health consequences make it important that the team be as accurate as possible in its forecasts.

An interview with one of the primary forecasters, and follow up discussions with team members, revealed that the team feels that its primary responsibility is to public health and that forecast errors should favor public health. This means that, when in doubt, the team biases its forecasts upwards to issue a higher forecast and err on the side of calling a smog alert. In other words, all else equal, we expect the team’s forecasts to be positively biased.

However, we argued earlier that use of visual representation technologies will engage imagery processing enhancing information accessibility; that is, the perceived ease with which information is processed. Greater feelings of ease of processing, in turn, will raise belief confidence. In other words, the metacognition of feeling that imagery information is easier to process will lead to inferences that the information is more persuasive and true (Lee 2004). If teams are more confident in their forecasts, they should be less likely to bias their forecasts in a particular direction in order to mitigate the consequences of being wrong. In the context we study, this means that greater use of visual representation technologies should be associated with less positively biased forecasts.

Whether use of visual representation technologies will also increase forecast accuracy is an open question. Although imagery processing should increase the persuasiveness of information, and confidence in this information, it is unclear whether this means that teams will do a better job in interpreting information and making better forecasts. Nevertheless, if forecast bias is reduced, this should improve accuracy. This leads us to posit that:

HYPOTHESIS 4 (H4): *Greater use of visual representation technologies will be associated with a) Decreased forecasting bias; and b) Increased forecasting accuracy.*

2.3 Method

2.3.1 Research Setting

To evaluate our hypotheses, we collected daily chat data as well as predicted and actual air quality levels from a virtual smog forecasting team during the ground-level ozone season (May 1 to September 30) in Atlanta, Georgia, over a three-year period from 2006 to 2008. This data also allows us to examine the relationship between use of visual representation technologies and the bias and accuracy of team forecasts. The virtual smog forecasting team in our study is composed of ten research scientists at a major research university in Georgia and the state's environmental protection division (EPD). Team members include meteorologists, atmospheric scientists, a geochemist, and an expert in statistics, and are located in various parts of the region. The team uses a custom website to access information technologies used to make forecasts. These technologies include text-based weather forecasts, interactive graphical contour plots and maps, current readings from air sensing devices in the area, satellite imagery, and regression and other statistical models. An example of a visual representation technology in this setting is a contour weather map; an example of a non-visual technology is a weather diagnostic tool (shown in Figure 2.1 and Figure 2.2). Table A.1 in Appendix A provides details on the portfolio of information technologies available to the team.

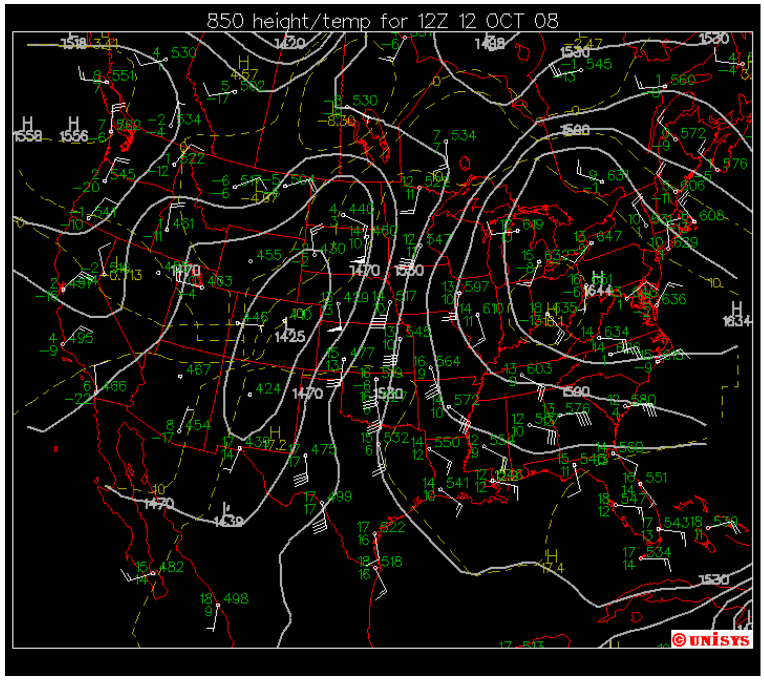
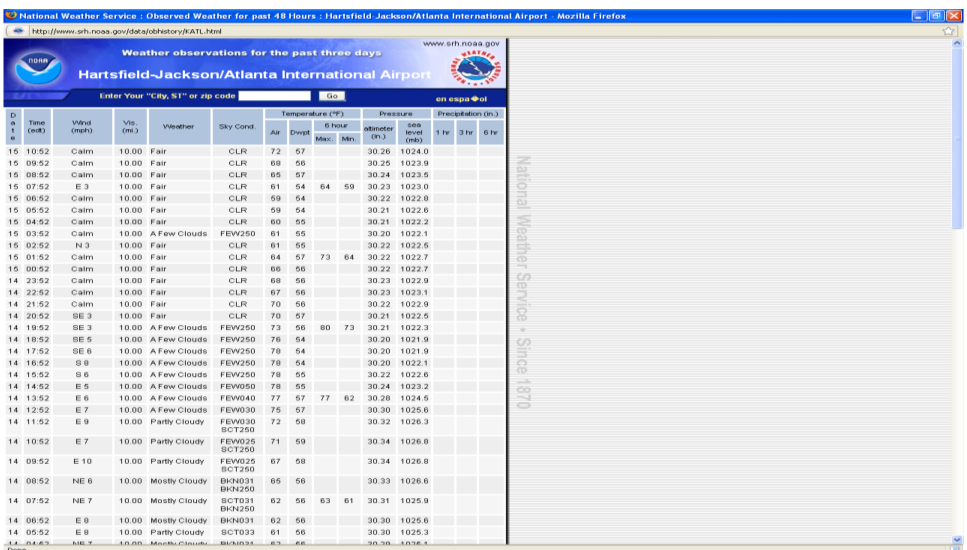


Figure 2.1: Visual Representation Technology Example


National Weather Service : Observed Weather for past 48 Hours : Hartsfield-Jackson/Atlanta International Airport - Mozilla Firefox

http://www.srh.noaa.gov/data/obhistory/KATL.html

www.srh.noaa.gov

Weather observations for the past three days

Hartsfield-Jackson/Atlanta International Airport

Enter Your "City, ST" or zip code Go

en espa�ol

Date	Time (edt)	Wind (mph)	Vis. (mi.)	Weather	Sky Cond.	Temperature (°F)				Pressure		Precipitation (in.)		
						Air	Dwpt	6 hour Max.	6 hour Min.	altimeter (in.)	sea level (mb)	1 hr	3 hr	6 hr
15	10:52	Calm	10.00	Fair	CLR	72	57			30.26	1024.0			
15	09:52	Calm	10.00	Fair	CLR	68	56			30.25	1023.9			
15	08:52	Calm	10.00	Fair	CLR	65	57			30.24	1023.5			
15	07:52	E 3	10.00	Fair	CLR	61	54	64	59	30.23	1023.0			
15	06:52	Calm	10.00	Fair	CLR	59	54			30.22	1022.8			
15	05:52	Calm	10.00	Fair	CLR	59	54			30.21	1022.6			
15	04:52	Calm	10.00	Fair	CLR	60	55			30.21	1022.2			
15	03:52	Calm	10.00	A Few Clouds	FEW250	61	55			30.20	1022.1			
15	02:52	N 3	10.00	Fair	CLR	61	55			30.22	1022.5			
15	01:52	Calm	10.00	Fair	CLR	64	57	73	64	30.22	1022.7			
15	00:52	Calm	10.00	Fair	CLR	66	56			30.22	1022.7			
14	23:52	Calm	10.00	Fair	CLR	68	56			30.23	1022.9			
14	22:52	Calm	10.00	Fair	CLR	67	56			30.23	1023.1			
14	21:52	Calm	10.00	Fair	CLR	70	56			30.22	1022.9			
14	20:52	SE 3	10.00	Fair	CLR	70	57			30.21	1022.5			
14	19:52	SE 3	10.00	A Few Clouds	FEW250	73	56	80	73	30.21	1022.3			
14	18:52	SE 5	10.00	A Few Clouds	FEW250	76	54			30.20	1021.9			
14	17:52	SE 6	10.00	A Few Clouds	FEW250	78	54			30.20	1021.9			
14	16:52	S 8	10.00	A Few Clouds	FEW250	78	54			30.20	1022.1			
14	15:52	S 6	10.00	A Few Clouds	FEW250	78	55			30.22	1022.6			
14	14:52	E 5	10.00	A Few Clouds	FEW050	78	55			30.24	1023.2			
14	13:52	E 6	10.00	A Few Clouds	FEW040	77	57	77	62	30.28	1024.5			
14	12:52	E 7	10.00	A Few Clouds	FEW030	75	57			30.30	1025.6			
14	11:52	E 9	10.00	Partly Cloudy	FEW030 SCT250	72	58			30.32	1026.3			
14	10:52	E 7	10.00	Partly Cloudy	FEW025 SCT250	71	59			30.34	1026.8			
14	09:52	E 10	10.00	Partly Cloudy	FEW025 SCT250	67	58			30.34	1026.8			
14	08:52	NE 6	10.00	Mostly Cloudy	BKN031 BKN250	65	56			30.33	1026.6			
14	07:52	NE 7	10.00	Mostly Cloudy	SCT031 BKN250	62	56	63	61	30.31	1025.9			
14	06:52	E 8	10.00	Mostly Cloudy	BKN031	62	56			30.30	1025.6			
14	05:52	E 8	10.00	Partly Cloudy	SCT033	61	56			30.30	1025.3			

National Weather Service • Since 1870

Done

Figure 2.2: Non-Visual Technology Example

The primary task of the team each day is to forecast the air quality (i.e., the level of ozone pollutant concentration measured in parts-per-billion [PPB] in the air) for the subsequent day in the Atlanta metropolitan area and surrounding cities during the ground-level ozone season (from May 1 to September 30). The U.S. Environmental Protection Agency (EPA) classifies different levels of air quality into six color zones, based on ozone concentration values. A value between 0-59 (green) is considered “good”; 60-75 (yellow) is “moderate”; 76-95 (orange) means “unhealthy for sensitive groups”; 96-115 (red) is “unhealthy”; 116-374 (purple) is “very unhealthy”; and over 374 (brown) is considered “dangerous,” but conditions in this range have never occurred in Georgia. In Atlanta, smog alerts are issued in three color zones: orange, red, and purple.

Every day at 1:30 p.m., during the ground-level ozone season, the smog forecasting team meets to discuss and reach consensus on the team’s ozone forecast for the following day. Because team members are geographically dispersed, and in different organizations, the meeting occurs in an Internet chat room. Before joining the chat room discussion, each individual team member uses the website to gather information and input his or her initial forecast. The average of the individual predictions serves as the team’s initial forecast of the next day’s ozone concentration. During the group chat room discussion, individual team members often defend or clarify their own predictions by referring to particular information technologies. The team reaches a consensus forecast through this online discussion. This forecast is posted on the State of Georgia’s Environmental Protection Division’s website by 2 p.m. and is sent to the news media by e-mail. If the team’s initial consensus is high, and individual forecasts are very similar to each other, the chat room discussion can last as little as five minutes. However, if initial team consensus is low, the chat room discussion can last up to 30 minutes. Figure 2.3 shows an example of an online chat discussion on a day when the team issued a smog alert. As can be seen in Figure 2.3, the team’s initial smog forecast is 93 (orange smog alert--unhealthy for sensitive groups). During the discussion, proponents of a higher forecast level use visual representation technologies to convince the team to raise the forecast to 96 (red alert--unhealthy for whole population). For instance, Forecaster A uses wind information from NAM to support the argument that the ozone level should be higher tomorrow. This leads others (e.g., Forecaster C) to agree to a higher level alert.

Forecast Conference Discussion
Forecaster A >> Avg=93/38, orange O3, high mod PM2.5 but violation Forecaster B >> avgs ok Forecaster C >> Average OK Forecaster A >> Surface winds really shut off tomorrow according to NAM Forecaster C >> NGM Too. Forecaster D >> I not sure I see any reason for PM to edge lower the next 24 hours. What we have now is what we will start with in the morning. And now we are at 40+ at some sites. Forecaster A >> And Fort Mtn already in orange this AM. Forecaster C >> I can see going higher Forecaster A >> I like 96/41 myself Forecaster A >> I'm good with 96/41 Forecaster E >> I see the near stagnant winds for the morning, with at least some light flow for the afternoon... and the boundary layer looks to be a lot deeper than for today, and bufkit was hinting at afternoon convective clouds, which is pretty much the only reason why I didn't go red. Forecaster D >> 96/41 ok Forecaster C >> 96/41 OK Forecaster E >> yeah, go with 96/41 then. Forecaster A >> Agree with you on BL depth. Looked a little deeper than for today, but still showed poor ventilation relative to today. Forecaster A >> Ok then, 96/41 it is then, we'll go with red O3, orange PM2.5 Forecaster F >> 96/41 ok Forecaster B >> thanks, bye Forecaster D >> thanks - good day to work inside tomorrow

Figure 2.3: Example of Daily Chat Room Discussion

2.3.2 Data Collection

2.3.2.1 Interview and Observation

To gain insight into the forecasting process, we conducted an initial interview with a key informant from the virtual team—one of the primary forecasters who is a research scientist at a major university in Atlanta. The interview was about one hour in length and was recorded. Interview questions were used to understand how forecasters make a prediction, which information they need in different situations, and so on. We also observed a meeting in which the team made a smog prediction after which we asked team members questions about the forecast process and recorded our observations of the meeting.

2.3.2.2 Archival Data

We obtained information about the actual observed ozone values for each day during the ground-level ozone season in 2006, 2007, and 2008 from the Ambient Monitoring Program (AMP) database of the Georgia Environmental Protection Division. From the smog forecasting website used by the team, we extracted: (1) initial individual forecasts of the next day's ozone concentration, (2) the team's final consensus forecast, and (3) the text of the team's online chat.

2.3.3 Dependent Variables

2.3.3.1 Use of Visual Representation Technologies

To assess the extent of use of visual representation technologies, we first examined the full range of the 23 technologies available to the team and classified technologies as visual representations or non-visual tools. Appendix A provides details on this classification and characteristics of each technology. A technology was coded as a "visual representation" if it included a graph or map. For example, the 850mb Map shown in Figure 2.1 is coded as a visual representation technology while the Weather

Diagnostic Tool in this figure is coded as a non-visual tool. To verify this coding, we computed the amount of information presented simultaneously by, and interactivity level for, each technology—key distinguishing features of visual representation technologies (Card et al. 1999; Thomas and Cook 2005; see Appendix A). A multivariate GLM analysis revealed a significant difference in these characteristics for our coded visual representation versus non-visual technologies (Wilk's $\lambda = 0.59$, $F(2, 20) = 7.08$, $p < .01$). In addition, separate GLM analyses show that technologies coded as visual representations present significantly more information ($F(1, 21) = 11.82$, $p < .01$) and have significantly higher levels of interactivity ($F(1, 21) = 11.30$, $p < .01$) than non-visual coded technologies. Both analyses confirm the validity of our coding of the technologies.

We calculated the extent of use of visual representation technologies by the team on a particular day as the number of visual representation technologies used during the team's chat room discussion that day divided by the total number of information technologies used during the discussion (*RATIO OF VISUAL IT USE*). This ratio controls for potential differences in the number of technologies used on a given day. For example, in the chat room discussion shown in Figure 2.3, the team used three visual representation technologies (NGM, NAM, and Bufkit) and one non-visual technology (the chat room itself), so the ratio of visual representation technology use on that day was 75%. The percentage is multiplied by 100 for ease of interpretation.

2.3.3.2 Team Performance

We take advantage of the available data to examine the potential relationship between use of visual representation technologies and forecasting performance. Bias and accuracy were computed using the actual observed value of ozone concentration for a particular day (obtained from the Georgia EPD) and the team's prediction for that day (obtained from the team's chat room discussion). As noted earlier, *BIAS* is measured as the difference between the predicted and actual ozone level. For example, the team's ozone level prediction for July 19, 2008, in the chat room discussion shown in Figure 2.3 is 96 PPB. The actual ozone level on July 19, 2008, was 75 PPB. Thus, the *BIAS* of this forecast is 21 (i.e., the team over-predicted the ozone level for the following day by +21 PPB). In contrast, accuracy is measured as the absolute value of the difference between the predicted and actual ozone level. Since smaller numbers denote a more accurate forecast, our variable measures the *INACCURACY* of the team forecast. In the example in Figure 2.3, the *INACCURACY* is 21 (i.e., the predicted ozone level was within 21 PPB of the actual).

2.3.4 Independent Variables

2.3.4.1 Team Consensus

Following prior research on measuring consensus in forecasts (Lahiri and Teigland 1987), the level of initial team consensus (*LACK OF CONSENSUS*) was measured as the variance in the initial individual forecasts on a given day. For example, the variance in the initial predictions for July 19, 2008, depicted in the chat room discussion shown in Figure 2.3 is 27.20 PPB.

2.3.4.2 Environmental Exactingness

The background interview and discussion after observing the team forecasting process revealed that team members perceive forecasts near the yellow-orange and orange-red borders as the most exacting. The yellow-orange border is seen as exacting, since it potentially involves issuing a smog alert for sensitive individuals, and the orange-red border is seen as even more exacting since the economic and health consequences of making an error in issuing or failing to issue a smog alert for the general population are even larger in this zone. The team did not express similar concerns about predictions at the green-yellow border as this border does not involve a smog alert. Accordingly, we used two binary variables to represent exactingness and coded *EXACTINGNESS(YO)* as "1" if the initial team perception was within 5 parts-per-billion (PPB) of the yellow-orange border and *EXACTINGNESS(OR)* as "1" if the initial team perception was within 5 PPB of the orange-red border; "0" otherwise. For example, in Figure 2.3, since the team's initial forecast was 93 PPB (which is within 5 PPB of the orange-red border), we coded the environmental exactingness for this day as *EXACTINGNESS(OR)* = 1.

2.3.5 Control Variables

Given that team size (*TEAM SIZE*) can affect both technology choice and performance (Easley et al. 2003; Gibson and Cohen 2003; Yetton and Bottger 1983), we include team size by counting the number of forecasters who posted an initial forecast.

To control for differences in ground-level ozone concentrations on weekdays versus weekends, as well as month and year effects, (U.S. Environmental Protection Agency 2003), we coded *WEEKDAY* as "1" for Monday to Friday and "0" otherwise. We used four binary variables, *JUNE*, *JULY*, *AUGUST*, and *SEPTEMBER*, to distinguish these months from the base month of May. We used two binary variables, *YEAR2007* and *YEAR2008*, to distinguish these years from the base year of 2006.

Because performance is likely to be affected by team effort (*EFFORT*; (e.g., Todd and Benbasat 1999)), we control for effort by counting the number of words in the online chat on a given day. For example, for the day depicted in Figure 2.3, the number of words in the online chat is 289, yielding a measure of 289 for *EFFORT* on that day.

2.4 Analysis and Results

The data on technology choices, environmental exactingness, team consensus, and the observed ozone concentration levels for each day in the ozone season in each year yielded a total of 457 daily observations from 2006-2008. Table 2.1 reports the means, standard deviations, and correlations of the variables in the analysis. As shown in Table 2.1, pair-wise correlations between the variables in our analysis are modest with almost all well below 0.50. Table 2.1 also reveals that the average ratio of visual representation technology use is 23%, and the average team size is five members on a typical day.

2.4.1 Use of Visual Representation Technologies

We used hierarchical OLS regression analysis to estimate the effects of team consensus and environmental exactingness on use of visual representation technologies (*RATIO OF VISUAL IT USE*) as shown in Equation 1 below. First, we entered the control variables, then added the variables for consensus level and environmental exactingness, and finally added the interaction effects between consensus level and environmental exactingness. This approach allows us to more easily evaluate the incremental variance explained due to particular factors.

$$
\begin{aligned}
&\text{RATIO of VISUAL IT USE} = \\
&\beta_0 + \beta_1\text{WEEKDAY}+\beta_2\text{JUNE}+\beta_3\text{JULY}+\beta_4\text{AUGUST}+\beta_5\text{SEPTEMBER}+ \\
&\beta_6\text{YEAR2007}+\beta_7\text{YEAR2008} +\beta_8\text{TEAM SIZE}+\beta_9\text{LACK of CONSENSUS}+ \\
&\beta_{10}\text{EXACTINGNESS(YO)}+\beta_{11}\text{EXACTINGNESS(OR)}+ \\
&\beta_{12}\text{LACK of CONSENSUS*EXACTINGNESS(YO)}+ \\
&\beta_{13}\text{LACK of CONSENSUS*EXACTINGNESS(OR)}+\varepsilon
\end{aligned}
\qquad \textbf{(1)}
$$

As can be seen in the last two columns of Table 2.2, the control variables, *WEEKDAY*, *JUNE*, *JULY*, *YEAR2007*, *YEAR2008*, and *TEAM SIZE* are significant. *WEEKDAY* has a positive and significant coefficient, suggesting greater use of visual representation technologies on weekdays relative to weekends. *JUNE* and *JULY* have positive and significant coefficients, suggesting more use of visual representation technologies in June and in July relative to in May. *YEAR2007* and *YEAR2008* are positive and significant, suggesting greater use of visual representation technologies in 2007 and 2008 relative to 2006. *TEAM SIZE* has a positive coefficient, suggesting that the greater the number of participants in a chat room discussion the greater their use of visual representation technologies. Adding the main effects of initial consensus and exactingness to the model significantly improves variance explained ($\Delta R^2 = 0.04$, $F = 6.24$, $p < 0.01$).

To evaluate our first two hypotheses, we followed the standard statistical procedure (e.g., Greene (2003)) to test main effects in the full model. This requires differentiating Equation 1 with respect to the particular effect and then substituting the mean value of the interacting effect. To test Hypothesis 1, that lower initial team consensus is associated with greater use of visual representation technologies, this is ∂*RATIO OF VISUAL IT*

USE / ∂*LACK OF CONSENSUS* = $\beta_9 + \beta_{12}$ * *EXACTINGNESS(YO)* + β_{13} * *EXACTINGNESS(OR)* = 0.05+0.22*0.25+0.18*0.05 = 0.11. Following Greene (2003) the standard error for the coefficient is 0.03, yielding a t value of 3.67, $p < 0.01$. Thus, we find a significant positive relationship between initial team consensus and use of visual representation technologies, and Hypothesis 1 is supported.

Hypothesis 2 postulated that more exacting environments are associated with greater use of visual representation technologies. A joint test of *EXACTINGNESS(YO)* and *EXACTINGNESS(OR)*, yields an F-value of 5.10, $p < 0.01$, showing that, overall, in more exacting environments the team significantly increases its *RATIO OF VISUAL IT USE*. In sum, Hypothesis 2 is supported.

Hypothesis 3 posited a moderating relationship between initial team consensus level and environmental exactingness on use of visual representation technology, such that at lower levels of consensus, exacting environments would be associated with greater use of such technologies. As can be seen in Table 2.2, and supporting Hypothesis 3, the interaction effects are both positive and significant ($\beta_{12} = 0.22$, $p < 0.01$; $\beta_{13} = 0.18$, $p < 0.05$). Moreover, adding the interaction effects to the model explains significant incremental variation in use of visual representation technology ($\Delta R^2 = 0.01$, $F = 3.16$, $p < 0.05$).

Table 2.1: Means, Standard Deviations, and Correlations

	Mean	S.D.	1	2	3	4	5	6	7
1. Bias	2.62	11.75	1.00						
2. Inaccuracy	9.48	7.40	0.40**	1.00					
3. Ratio of Visual IT Use	23.46	30.54	-0.07	0.03	1.00				
4. Effort	147.46	98.16	0.06	0.05	0.48**	1.00			
5. Lack of Consensus(VC)	31.90	34.65	-0.08	-0.01	0.14**	0.17**	1.00		
6. Exactingness(YO)	0.25	0.43	0.08†	0.05	0.03	0.18**	-0.16**	1.00	
7. Exactingness(OR)	0.05	0.22	0.11*	0.11*	0.19**	0.25**	0.05	-0.13**	1.00
8. Weekday	0.72	0.45	-0.07	0.00	0.12**	0.10*	-0.01	0.04	0.02
9. June	0.20	0.40	-0.05	0.05	0.16**	0.07	0.14**	0.05	0.11*
10. July	0.20	0.40	0.04	0.11*	0.11*	0.02	-0.04	0.02	0.08
11. August	0.20	0.40	0.01	0.01	0.01	0.14**	-0.07	0.14**	0.05
12. September	0.20	0.40	0.08†	-0.04	-0.18**	-0.16**	0.03	-0.18**	-0.12*
13. Year2007	0.33	0.47	0.03	0.06	0.11*	0.21**	0.02	-0.02	0.04
14. Year2008	0.34	0.47	0.01	-0.04	0.05	0.01	-0.05	0.05	-0.04
15. Team Size	4.91	1.29	-0.07	-0.04	0.13**	0.25**	-0.02	0.00	0.02

	8	9	10	11	12	13	14	15
8. Weekday	1.00							
9. June	-0.01	1.00						
10. July	-0.01	-0.25**	1.00					
11. August	0.00	-0.25**	-0.26**	1.00				
12. September	-0.02	-0.25**	-0.25**	-0.25**	1.00			
13. Year2007	0.01	0.00	0.00	0.00	0.00	1.00		
14. Year2008	-0.01	0.00	0.00	0.00	0.00	-0.50**	1.00	
15. Team Size	0.22**	-0.11*	0.11*	0.03	-0.10*	-0.16**	-0.09†	1.00

N = 457. ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$. Coding: Exactingness(YO): 1 = initial team forecast is within 5 parts-per-billion (PPB) of the yellow-orange border, 0 = otherwise; Exactingness(OR): 1 = initial team forecast is within 5 PPB of the orange-red border, 0 = otherwise; Weekday: 1 =

from Monday to Friday, 0 = otherwise; June: 1 = date is in June, 0 = otherwise; July: 1 = date is in July, 0 = otherwise; August: 1 = date is in August, 0 = otherwise; September: 1 = date is in September, 0 = otherwise; Year2007: 1 = date is in year 2007, 0 = otherwise; Year2008: 1 = date is in year 2008, 0 = otherwise; variables are unstandardized.

Table 2.2: Use of Visual Representation Technology

	Control Variables Only		With Main Effects		With Main Effects and Interactions	
Independent Variables	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Intercept β_0	-14.74	-2.17*	-18.03	-2.67**	-14.84	-2.15*
Weekday β_1	6.14	2.05*	6.02	2.07*	6.61	2.28*
June β_2	17.56	3.87**	13.86	3.06**	13.46	2.96**
July β_3	12.11	2.87**	10.19	2.36*	10.39	2.40*
August β_4	6.95	1.62	5.27	1.21	4.73	1.08
September β_5	-3.57	-0.92	-3.99	-1.01	-4.27	-1.09
Year2007 β_6	14.61	4.31**	14.35	4.35**	14.39	4.37**
Year2008 β_7	11.35	3.42**	11.91	3.66**	11.39	3.53**
Team Size β_8	3.77	3.41**	3.72	3.41**	3.52	3.24**
Lack of Consensus(VC) β_9			0.11	2.95**	0.05	1.07
Exactingness(YO) β_{10}			1.94	0.60	-3.85	-1.01
Exactingness(OR) β_{11}			19.61	3.21**	12.94	1.73†
VC_YO β_{12}					0.22	3.12**
VC_OR β_{13}					0.18	2.21*
R^2	0.13		0.16		0.18	
R^2 Change	0.13		0.04		0.01	
F Change	8.26**		6.24**		3.16*	

N = 457. ** p <0.01, * p < 0.05, † p < 0.10. VC_YO = Lack of Consensus*Exactingness(YO); VC_OR = Lack of Consensus*Exactingness(OR)

Table 2.3: Impact of Visual Representation Technology Use on Performance

	Inaccuracy				Bias			
	Control Variables Only		With Main Effects		Control Variables Only		With Main Effects	
Independent Variables	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
Intercept β_0	8.59	4.88**	8.55	4.84**	4.39	1.51	4.06	1.40
Weekday β_1	0.05	0.06	0.08	0.10	-1.81	-1.52	-1.55	-1.29
June β_2	2.31	2.17*	2.37	2.21*	-0.02	-0.01	0.46	0.27
July β_3	3.20	3.33**	3.25	3.32**	2.25	1.34	2.68	1.58
August β_4	1.55	1.47	1.56	1.47	0.84	0.51	0.90	0.54
September β_5	1.35	1.35	1.33	1.33	4.30	2.84**	4.14	2.70**
Year2007 β_6	0.55	0.61	0.58	0.63	0.04	0.03	0.24	0.16
Year2008 β_7	-0.38	-0.44	-0.35	-0.40	-0.09	-0.07	0.15	0.11
Team Size β_8	-0.28	-0.88	-0.28	-0.87	-0.64	-1.28	-0.63	-1.24
Lack of Consensus (VC) β_9	0.00	-0.13	-0.00	-0.13	-0.03	-1.41	-0.03	-1.44
Exactingness(YO) β_{10}	0.76	0.75	0.72	0.70	1.99	1.28	1.63	1.06
Exactingness(OR) β_{11}	4.78	2.04*	4.78	2.03*	9.23	2.49*	9.25	2.51*
VC_YO β_{12}	0.01	0.28	0.01	0.30	0.04	1.01	0.04	1.20
VC_OR β_{13}	-0.05	-1.32	-0.05	-1.28	-0.07	-1.58	-0.06	-1.53
Effort β_{14}	0.00	0.21	0.00	0.32	0.01	1.10	0.01	1.80†
Ratio of Visual IT Use β_{15}			-0.01	-0.41			-0.04	-2.08*
R^2	0.05		0.05		0.06		0.07	
R^2 Change	0.05		0.00		0.06		0.01	
F Change	1.56†		0.16		2.17**		4.33*	

N = 457. ** p < .01, * p <.05, † p < 0.10. VC_YO = Lack of Consensus* Exactingness(YO); VC_OR = Lack of Consensus* Exactingness(OR)

2.4.2 Impacts of Visual Representation Technologies on Performance

To examine the effects of use of visual representation technologies on performance, hierarchical regression analyses were conducted. In particular, we estimated the effects of use of visual representation technologies on *BIAS* and *INACCURACY* with the following regression models:

$$\begin{aligned}
&\text{BIAS} = \\
&\beta_0 + \beta_1\text{WEEKDAY}+\beta_2\text{JUNE}+\beta_3\text{JULY}+\beta_4\text{AUGUST}+\beta_5\text{SEPTEMBER}+ \\
&\beta_6\text{YEAR2007}+\beta_7\text{YEAR2008} +\beta_8\text{TEAM SIZE}+\beta_9\text{LACK of CONSENSUS}+ \\
&\beta_{10}\text{EXACTINGNESS(YO)}+\beta_{11}\text{EXACTINGNESS(OR)}+ \\
&\beta_{12}\text{LACK of CONSENSUS*EXACTINGNESS(YO)}+ \\
&\beta_{13}\text{LACK of CONSENSUS*EXACTINGNESS(OR)}+ \\
&\beta_{14}\text{EFFORT}+\beta_{15}\text{RATIO of VISUAL IT USE}+\varepsilon
\end{aligned} \quad \textbf{(2)}$$

$$\begin{aligned}
&\text{INACCURACY} = \\
&\beta_0 + \beta_1\text{WEEKDAY}+\beta_2\text{JUNE}+\beta_3\text{JULY}+\beta_4\text{AUGUST}+\beta_5\text{SEPTEMBER}+ \\
&\beta_6\text{YEAR2007}+\beta_7\text{YEAR2008} +\beta_8\text{TEAM SIZE}+\beta_9\text{LACK of CONSENSUS}+ \\
&\beta_{10}\text{EXACTINGNESS(YO)}+\beta_{11}\text{EXACTINGNESS(OR)}+ \\
&\beta_{12}\text{LACK of CONSENSUS*EXACTINGNESS(YO)}+ \\
&\beta_{13}\text{LACK of CONSENSUS*EXACTINGNESS(OR)}+ \\
&\beta_{14}\text{EFFORT}+\beta_{15}\text{RATIO of VISUAL IT USE}+\varepsilon
\end{aligned} \quad \textbf{(3)}$$

Table 2.3 displays the results of these estimates. We first evaluated the results for *BIAS*. In the first step of our estimation of Equation 2**,** we entered all control variables from the first stage regressions. To separate the performance effects of use of visual representation technologies from decision making effort (Todd and Benbasat 1999), we include team effort (*EFFORT*) in the first step. In the second step, adding *RATIO OF VISUAL IT USE* resulted in a significant increase in variance explained ($\Delta R^2 = 0.01$, $F = 4.33$, $p < 0.05$). Finally, we regressed *INACCURACY* on the same set of variables to estimate Equation 3. However, *RATIO OF VISUAL IT USE* was not a significant predictor of *INACCURACY*. Supporting Hypothesis 4a, but not 4b, we find a significant effect for bias (t = -2.08, p < 0.05) but not inaccuracy (t = -0.41, p > 0.10). In particular, an increase in the use of visual representation technologies is associated with a reduction in the bias of the team's forecast, but greater use of visual representation technology did not help the team improve the accuracy of its forecast.

2.4.3 Robustness Analyses

We conducted a number of analyses to verify the robustness of our results. Given the time-series nature of the data, we evaluated whether serial correlation was an issue. Using the Cochrane-Orchutt procedure to correct for potential serial correlation, we re-estimated equations [1], [2], and [3]; these results (shown in Tables B.1 to B.3 in Appendix B) produce estimates consistent with those obtained from ordinary least squares regression, leading us to conclude that serial correlation is not an issue in our data.

Given our two-stage model, with the first stage predicting use of visual representation technologies, and the second stage associating use of visual representation technologies with performance, we investigated the possibility that use of visual representation technologies is endogenous. We note that the temporal nature of the data (in which the predictors of technology use temporally precede use of visual representation technologies in the online chat, and the performance outcomes associated with use of visual representation technologies proceed from use of these technologies) reduce the possibility of endogeneity. Nevertheless, we conducted several analyses to discern whether endogeneity issues are salient. The first analysis is a test for endogeneity (as described in

Wooldridge 2006). The Wooldridge test involves regressing *RATIO OF VISUAL IT USE* on all exogenous variables. The residuals from this estimation are saved and added as a variable to the second stage (performance) equations. If the coefficient on this variable is significant, this suggests that *RATIO OF VISUAL IT USE* is endogenous, and if not, it suggests there is no endogeneity issue. In our analysis, the coefficient on this variable is significant in neither the Bias nor the Inaccuracy equation ($\delta_1 = 0.02$; t-value = 0.37; $p > 0.10$ for Bias; $\delta_1 = -0.03$; t-value = -0.86; $p > 0.10$ for Inaccuracy), suggesting that *RATIO OF VISUAL IT USE* is *not* endogenous in either equation.

The second analysis is an instrumental variables analysis, in which we constructed an instrument for use of visual representation technologies using an information theoretic measure of the average amount of information provided by all (visual and non-visual) technologies used on a particular day (see Appendix A). This measure meets all of the required properties of an instrumental variable (Kennedy 1992, p. 139): it is significantly correlated with *RATIO OF VISUAL IT USE* ($r = 0.94$, $p < 0.001$) but it is not correlated with the residuals in either of the two performance equations ($r_{bias} = -0.01$, $p > 0.10$; $r_{accuracy} = 0.01$, $p > 0.10$). Adding this instrument to equation [1], we used two-stage least squares (2SLS) to estimate equations [1] and [2] and then equations [1] and [3]. The results are shown in Tables B.1 to B.3 in Appendix B. As can be seen in these tables, the estimates of the instrumental variable regressions are consistent with those for ordinary least squares, suggesting that use of visual representation technologies is not endogenous in our analysis.

As a final check, we considered the possibility that the team may proportionately use more visual representation technologies as their choice set includes a greater number of visual than non-visual technologies. Thus, use of visual representation technologies may need to be corrected for chance. Following Lurie (2004), we computed the corrected ratio of visual information technology use using the equation: $\overline{P}_i = (P_i - P_{ic}) / (1 - P_{ic})$, where $\overline{P}_i$ = the ratio of visual representation technology use adjusted for chance, P_i = the ratio of visual representation technology use by chance alone, and P_{ic} = the observed ratio of visual representation technology use unadjusted for chance factors. In order to easily interpret and compare with OLS results, we transformed the corrected ratio for each observation so that it had the same range and scale as our original measure, and multiplied each transformed value by 100. Using the corrected measure in place of our original measure, we re-estimated equations [1], [2], and [3]. The results from these estimations (shown in Tables B.1 to B.3 in Appendix B) are consistent with those obtained from ordinary least squares regression. Thus it is not the greater number of visual representation technologies available to the team that is driving our results, but rather the team's proportionate use of these technologies which varies based on the information requirements of each day.

2.5 Discussion and Conclusions

Despite a dramatic increase in the availability of visual representation technologies to virtual teams in medicine, science, business, government agencies, and the military (Card et al. 1999; Thomas and Cook 2005), little is known about their role in virtual teams. In this paper we propose that, in addition to providing decision makers with rich images of data, visual representation technologies play an important persuasive role in helping virtual teams reach consensus; particularly in exacting environments in which the consequences for error are large. Drawing on a growing body of research on the role of imagery processing in persuasion (Chaiken and Trope 1999; Kahneman and Frederick 2005; Sloman 1996), we hypothesize that virtual teams will use more visual representation technologies when they need to reach consensus and when highly exacting contexts increase their need for confidence in their decisions. Results from our three-year study of the virtual team responsible for forecasting ozone levels and issuing smog alerts for the 5-million person Atlanta region show that the team's use of visual representation technologies depends on the exactingness of the decision context and the extent to which team members are in agreement. In particular, the team increases its use of technologies for visual representation, such as maps, satellite, and radar imagery, when initial team consensus is low and when facing exacting environments in which the consequences of judgment errors are large. Our results suggest that an initial forecast in the yellow-orange border increases use of visual representation technologies by 3.2% while an initial forecast in the orange-red border increases use of these technologies by 18.7%. Further, for each 1 PPB increase in lack of consensus (i.e., in the variance of the initial PPB predictions by individual team members) there is a .11% increase in use of visual IT. The effects of low team consensus on use of visual representation technologies are magnified under high exactingness. Figures 2.4 and 2.5 graph the interactions between team consensus and exactingness at the yellow-orange (YO) and orange-red (OR) borders and show that use of tools for visual representation doubles when team consensus is low and environmental exactingness is high. This is true at both the yellow-orange and orange-red borders for issuing smog alerts. Finally, our results also provide some support for the idea that using visual representation technologies can improve performance. In particular, bias is reduced as use of visual representation technologies increases. However, accuracy seems unaffected by use of visual representation technologies.

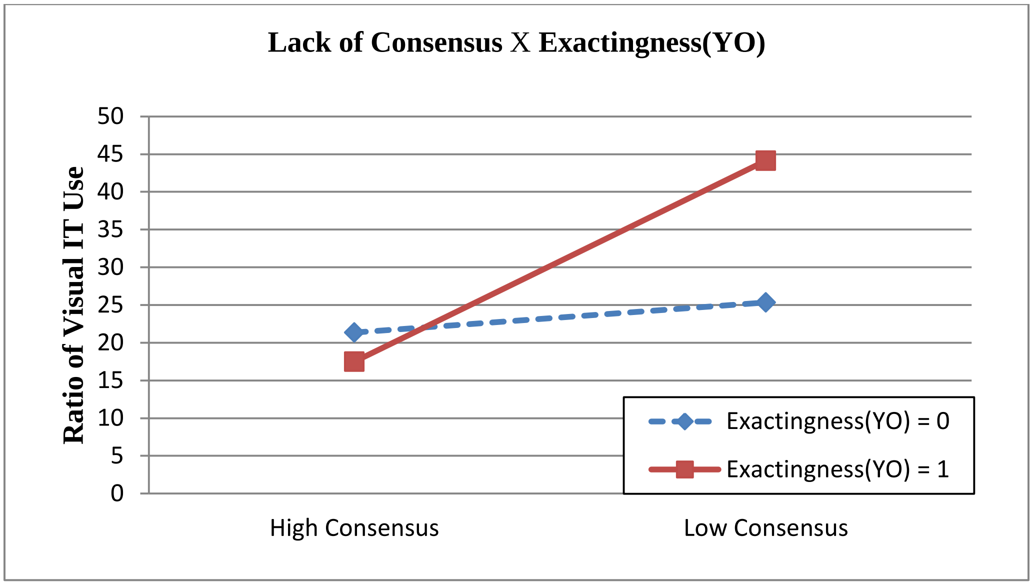


Figure 2.4: Interaction between Lack of Consensus and Exactingness(YO)

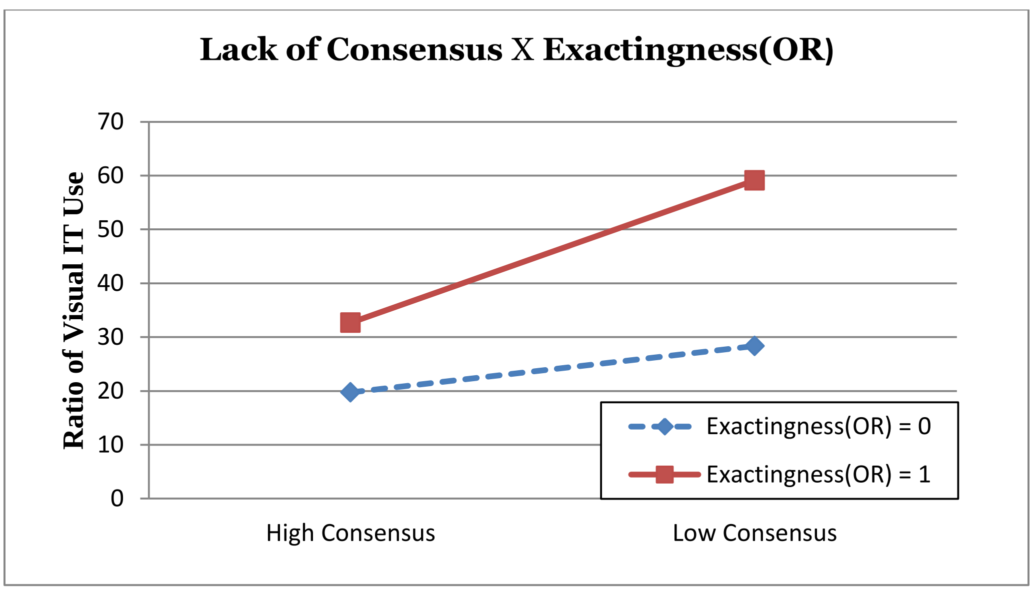


Figure 2.5: Interaction between Lack of Consensus and Exactingness(OR)

Consistent with our theorizing, results suggest that, by engaging imagery processing, use of visual representation technologies can help virtual teams reach consensus; particularly when the consequences of making incorrect judgments loom large. Through transportation into the narrative world, increased accessibility of imagery information, and neural activation similar to that observed when images are viewed, use of visual representation technologies should enhance persuasion and information believability. This, in turn, should raise team confidence and reduce decision bias; in the context we study, a tendency to over predict smog levels in the interest of public safety. Our results suggest that use of visual representation technologies may help address some of the limitations of virtual team environments that lead to differences in virtual team members' interpretation of information, lack of cues to information importance, and difficulties in understanding the contexts in which other team members act (Cramton 2001). Use of visual representation technologies appears to address these limitations, however, by changing the way in which information is processed rather than by increasing communication channels or social presence. Future research might compare use of visual representation technologies to other approaches to improving virtual team processes.

Although an increase in use of visual representation technologies reduced the bias (i.e., the extent of over prediction) in team forecasts, it did not significantly increase the accuracy of forecasts. As can be seen in Figure 2.6 (which graphs forecasted predictions from equation [2] against *RATIO OF VISUAL IT USE*), when the team uses no visual representation technology, team members over predict the level of ozone concentration more than 90% of the time. As shown by the simple smoothed line in Figure 2.6 (which is the predicted bias when all of the independent variables are at their mean values), when

RATIO OF VISUAL IT USE reaches 50%, bias trends towards zero. However, as *RATIO OF VISUAL IT USE* approaches 100%, the team increasingly tends to under predict ozone levels. This may explain why accuracy is unaffected (i.e., the amount of over-prediction at very low levels of use of visual representation technologies is compensated by the amount of under-prediction at very high levels of use). Given that the team tends to err on the side of public health, and therefore over predict ozone levels, use of visual representation technologies may reduce bias by increasing team confidence in their forecasts. At the same time, the failure to observe significant improvement in accuracy with increased use of visual representation technologies suggests that engaging imagery processing is not a panacea for virtual teams. In particular, because visual representation technologies help decision makers see *imagined* as well as real patterns in data (Lurie and Mason 2007), use of such technologies may increase team confidence without necessarily increasing performance. Future research could examine these issues by studying how use of visual representation technologies affects subjective as well as objective measures of decision quality.

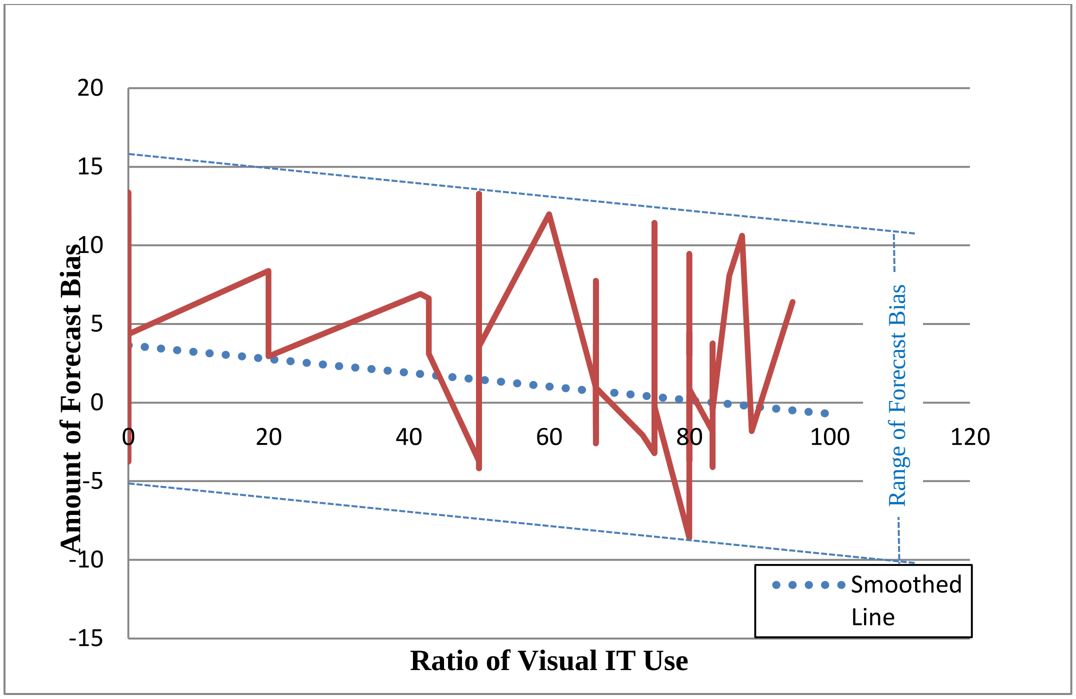


Figure 2.6: Forecast Bias (Predicted)

Our study makes a number of theoretical and managerial contributions. In arguing how use of different information technologies may lead virtual teams to engage different psychological processes, we add to prior work focused on how teams use different technologies to meet their communication needs (Massey and Montoya-Weiss 2006; Miranda and Saunders 2003; Straub and Karahanna 1998; Watson-Manheim and Bélanger 2007). Because imagery processing changes the way virtual teams understand and respond to information, use of visual representation technologies is likely independent from the use of technologies for team communication; indeed, for the team studied here, the technology for communication (a chat room) remains constant. More generally, this research points to the need for additional study of how information technologies affect the way teams "think." By studying the technology use and associated performance of an expert virtual team, making real, time-constrained, and consequential choices over a three year period, we also add to prior research conducted using single shot scenarios in which novice decision makers work with a single technology and face a relatively sparse amount of information (Hastie 2001; Klein et al. 1995).

Our results also suggest that use of technologies for information visualization changes the way that virtual teams reach consensus. Using or referring to the images presented by visual representation technologies may not only help individuals make sense of complex data (Card et al. 1999; Thomas and Cook 2005), but may also help virtual team members to persuade and reach consensus. At the same time, a tendency to envision false patterns in data may lead virtual teams to make incorrect inferences. Developing technologies that integrate non-visual analytical as well as visual information may help address some of the potential downsides of visual representations.

CHAPTER 3

INFLUENCE, INFORMATION TECHNOLOGY & GROUP POLARIZATION: A FIELD STUDY OF A VIRTUAL TEAM

3.1 Introduction

Does group discussion really help group members reach an unbiased consensus? During a discussion, group members can exchange factual information and share individual preferences to reconcile their differences. In addition, a group can combine information from multiple perspectives to avoid making a risky group decision. However, contrary to people's expectations, group members have a tendency to shift their initial positions/decisions in an extreme direction following a group discussion (Isenberg 1986). Such a tendency is called "group polarization." For example, jurors who initially favor a harsh penalty are more likely to decide on a harsher penalty after discussion, while jurors who initially favor a short sentence tend to decide on a shorter sentence after discussion (Sunstein, 2002).

In the academic field, group polarization has been considered an important and significant group phenomenon. Researchers from many disciplines, including jury decision making (MacCoun 1989), organizational behavior (Heath and Gonzalez 1995), information systems (Sia et al. 2002), marketing (Chandrashekaran et al. 1996), finance (Barber et al. 2003), political science (Stroud 2010), public policy (Paluck 2010), communication (Lee 2007), and economic decision making (Cason and Mui 1997), have taken an interest in group polarization. To enhance understanding of why group polarization occurs, researchers have identified several group processes and antecedents.

Prior studies have proposed that either one of two underlying mechanisms/processes can be used to explain group polarization: normative influence and informational influence (Isenberg 1986). In the first, group polarization takes place when individuals are motivated to present themselves in a socially favorable light. In the second, group polarization occurs when group members exchange persuasive arguments during their discussion. In addition to group processes, researchers have identified many antecedents of group polarization such as pre-discussion individual decisions (Butler and Crino 1992; Vinokur and Burnstein 1978a), risk level (Shupp and Williams 2008), group composition (Farrar et al. 2009), culture (El-Shinnawy and Vinze 1997), and media use (Lea and Spears 1991; Siegel et al. 1986).

Why do group members polarize their group decisions? Two points motivate our approach to this question. The first is the perspective of influence. Group members can make a group decision by using a single influence process (e.g., normative influence), but recent studies have underscored the importance of the interplay among various influences. The second is the perspective of technology. Information technologies are not only communication or decision making tools but are also persuasive tools that can be used to change one's opinions (Fogg 2003). These two motivations are linked to research on group polarization.

Past studies have focused on the investigation of antecedents. To date, however, we know little about the process of group polarization. Most of the past studies on group polarization have treated a group process as a "black box," but in this study, we attempt to open up this black box. The first goal of this study is to explore the interplay between informational influence and normative influence. Many researchers have investigated the effect of these influences on group polarization separately. That is, while some researchers have argued that informational influence is a sufficient and necessary process to explain group polarization, other researchers have reasoned that normative influence is a major process for judgmental tasks. However, to our knowledge, group polarization researchers have not studied the relative use of informational versus normative influence. Specifically, relative use is the ratio of the use of informational influence arguments to normative influence arguments. An investigation into relative use is very critical because the magnitude of group polarization may differ according to influence usage. In other words, a group with higher relative use during its discussion may experience a different magnitude of group polarization than a group with lower relative use.

Moreover, past studies have often considered technologies as either communication tools (e.g., Daft et al. 1987), or decision support tools (e.g., Todd and Benbasat 1999), or both (e.g., Zigurs et al. 1988). We know little about whether information technology can be used to persuade group members during a group discussion. Thus, the second goal of this study is to investigate the new role of information technology for persuasion in group polarization. Group members are more likely to shift or polarize their positions when receiving credible and persuasive information (Barber et al. 2003; Burnstein and Vinokur 1977; Isenberg 1986). Research on credibility has suggested that the credibility of information can increase because of source citations or references. For example, people are more likely to believe a tornado warning supported/cited by weather information technologies than they are a warning that is not supported/cited by such technologies. That is, a high intensity of informational references is associated with a high level of persuasiveness. Therefore, the intensity of information technology references and relative use may interact in their effect on the magnitude of group polarization. Another important factor that has not been analyzed in past studies is reference to information technology.

The third goal of this study is to examine when group members may adjust their relative use of informational influence versus normative influence. Since past studies have examined links between group polarization and its antecedents directly, our study complements these studies by exploring the relationships between antecedents and group processes. Two antecedents that may affect the relative use of informational influence versus normative influence are (1) the heterogeneity of pre-discussion individual decisions and (2) the uncertainty of the task. The goals of this study are consistent with a call by Sia et al. (2002) for research focusing on the group discussion process at a greater level of detail and a call by El-Shinnawy and Vinze (1998) for research investigating the relative importance of informational influence versus normative influence in virtual team settings.

In addition, we can further enhance knowledge about group polarization by including a field study. Most past studies have used controlled experiments to investigate group polarization. Because of experimental constraints, these experiments have focused on a single-shot task. Our study can complement these experiments by conducting a field study. Our field study allows us to investigate whether group polarization still takes place in a repeated task and time-constrained environment.

More knowledge about group polarization may be beneficial to group leaders or decision makers. Group polarization is a double-edged sword. On the one hand, group polarization can be favorable. For example, if a community, a city, or a country is seriously destroyed by a natural disaster (e.g., a tsunami, an earthquake, or a hurricane), individuals may be more generous when helping the victims after a social discussion (Muehleman et al. 1976). Thus, we could have expected group polarization to be very useful in fundraising activities for the March 11, 2011 earthquake in Japan, the fourth largest in the world, and for the May 12, 2008 earthquake in China, which caused over 69,000 fatalities and 18,000 missing. On the other hand, group polarization can be very harmful. For example, a weather forecasting group may initially issue a hurricane warning, but the group may then decide not to issue a warning after discussion. Such a decision might lead to enormous public health consequences if a warning was needed. Another example relates to an airline crash. According to the National Transportation Safety Board report, the reason that American Airlines Flight 1420 crashed on June 1, 1999, was that both pilots made a risky landing decision following a discussion. Therefore, exploring group polarization in more detail may encourage a group to make a favorable decision or discourage a group from making an unfavorable one.

Our research setting is well-suited for conducting a field study on group polarization. We investigated the group processes and information technology use of a virtual team responsible for forecasting ozone levels for the 5-million person Atlanta region in the United States. This natural research setting provides a rich context for examining the relative use of informational influence versus normative influence in an expert virtual team. The group’s forecasting task is relatively constant but the level of uncertainty varies from day to day. Over a two-year period, we observed individual predictions before discussion, the intensity of information technology references used to support forecasters’ arguments, and the magnitude of group polarization.

Our results reveal several interesting findings. First, we find that the relative use of informational influence versus normative influence is an important group process. The heterogeneity of pre-discussion individual decisions and task uncertainty cause group polarization through relative use. Surprisingly, we also find that relative use and the intensity of information technology references have a substitutive rather than complementary effect on group polarization.

3.2 Literature Review

3.2.1 Group Polarization

Before Stoner's (1961) classic study, the conventional wisdom had been that the members of a group would make riskier individual decisions than the group did. The supporting argument was that a group can combine information from different perspectives and prevent its members from making a risky decision. However, Stoner (1961) found the opposite. That is, a group is more likely to make a risky decision following a discussion than its typical or average group member. Researchers have called this phenomenon a risky shift. In addition, some researchers have found that, in some cases, a group decision moves toward a more cautious direction after discussion. Therefore, such movement has been called a cautious shift.

Researchers have considered either a cautious shift or a risky shift as group polarization. Group polarization has been defined as the inclination of making an extreme decision (risky or cautious) following group discussion (Isenberg 1986; Myers and Lamm 1976). However, an extreme decision does not indicate that group decisions have to move to one polar side. Researchers have suggested that an extreme decision is a within-group movement, not toward the middle of initial group members' preferences, but toward the initial tendency of those preferences (Butler and Crino 1992; Sunstein 2002).

Such a group's tendency can be explained by social comparison theory and persuasive argument theory. Social comparison theory posits that people are motivated to present themselves in a socially favorable light during group discussion (Baron and Roper 1976; Brown 1986). This motivation may lead to either a pluralistic balance behavior or a one-upmanship behavior (Isenberg 1986). A pluralistic balance behavior refers to a compromising behavior in which individuals present their positions between what they prefer and what their group prefers. A one-upmanship behavior is that individuals want to be distinct from as well as better than other people in a desirable direction. Therefore, group polarization results when most members of a group exhibit such behaviors, which are considered as normative influence.

In contrast, proponents of persuasive argument theory have suggested that only informational influence, not normative influence, is necessary and sufficient to cause group polarization (Burnstein 1982; Vinokur and Burnstein 1978b). The theory has argued that an individual's position is influenced by the number and persuasiveness of available arguments during group discussion. Persuasiveness can be determined by two components of an argument: novelty and validity (Isenberg 1986). Novelty of an argument is the level to which an argument can shed new insights. Validity is the level to which an argument is sound. Thus, group polarization is likely to occur when group members are exposed to more valid and/or novel arguments during a discussion. Such exposure of arguments is considered as informational influence.

Previous studies have debated whether group polarization can be better explained by two theories together. Some researchers have argued that persuasive argument theory alone is enough for the explanation of group polarization (Burnstein and Vinokur 1977; El-Shinnawy and Vinze 1998). These researchers also have argued that persuasive argumentation mediates the relationship between social comparison and group polarization. That is, social comparison is neither a necessary nor a sufficient condition. However, other scholars have suggested that social comparison theory and persuasive argument theory together are able to provide a better explanation for group polarization than either one alone (Isenberg 1986; Sia et al. 2002). For instance, a meta-analysis by Isenberg (1986) has suggested that both social comparison and persuasive argumentation co-occur during group discussion to produce group polarization, though the effect of persuasive argumentation is stronger than the effect of social comparison. Moreover, many scholars have proposed that both influences should be explored at the same time to effectively investigate group discussion (Butler and Crino 1992; Huang and Wei 2000; Kaplan and Miller 1987). Therefore, informational influence and normative influence could be considered important mechanisms which link group polarization and its antecedents.

3.2.2 Information Technology & Credibility

Past studies have investigated the different roles of information technologies. Most of the studies have considered information technologies as decision support and/or communication support tools. To effectively make a decision, people can use information technologies to facilitate information processing (e.g., Todd and Benbasat 1999). In addition, to clearly express their opinions, people can select technologies/media to convey different messages (e.g., Daft et al. 1987). Relatively few studies have examined the persuasive role of information technologies. Fogg and his colleagues have defined persuasive technologies as tools which are used to change one's attitude and behavior (Fogg 2003; Tseng and Fogg 1999). The tendency of the change is determined by the credibility level of information. That is, people are more likely to shift their decisions when receiving credible information.

Generally, credibility has been defined as believability (Tseng and Fogg 1999). Credible people are believable people; a credible message is a believable message. Moreover, Webster's dictionary defines credibility as "the quality or power of inspiring belief."

Credibility has been investigated in many academic disciplines such as communication (Metzger et al. 2003), information science (Hilligoss and Rieh 2008), marketing (Erdem and Swait 2004), and management information systems (Bhattacherjee and Sanford 2006; Poston and Speier 2005). Researchers from diverse disciplines together have enhanced our understanding of the concept of credibility. However, because these disciplines have their own goals, preferred methodologies, and backgrounds, such inconsistencies not only cause field-specific definitions of credibility but also lead to different focused dimensions of credibility (Rieh and Daniels 2007). Some disciplines (e.g., communication) have paid significant attention to source and media credibility, whereas others (e.g., information science) have focused on message credibility (Flanagin and Metzger 2007). That is, whether information is credible can be judged from either a source perspective or a message perspective. Although credibility can be examined from different perspectives, most researchers have considered credibility as a perceived characteristic of information (Wathen and Burkell 2002).

One stream of credibility research has suggested that source credibility is positively related to the perception of credible information. That is, sources with high credibility are more likely to create information that is perceived to be more credible than are sources with low credibility. Source credibility is determined by two key dimensions (Fogg et al. 2001; Self 1996). The trustworthiness dimension is defined as the extent to which a source is perceived to be well-intentioned, truthful, and unbiased. The expertise dimension, on the other hand, refers to the extent to which a source is perceived to be knowledgeable, experienced and competent.

In addition to these two dimensions, researchers have recognized that identifying the types of source credibility can enhance our understanding of how a source gains and loses its credibility. Tseng & Fogg (1999) have identified four types of source credibility. First, reputed credibility results from source labels. For instance, the source labeled Consumer Reports is perceived as more credible than the source labeled National Enquirer. Second, presumed credibility is based on the general assumptions of a perceiver. For example, people often have negative views of car salesmen and assume the salesmen are dishonest with low credibility. By contrast, people assume their friends are generally honest, so they consider such friends as credible sources. Third, surface credibility indicates the extent to which a perceiver believes a source by simply inspecting. For example, users judge a book by its cover. Finally, experienced credibility refers to the extent to which a perceiver believes a source by using first-hand experience.

For instance, interacting with sources over time can help people evaluate sources' credibility.

Another stream of credibility research tends to focus on the message rather than the source. This stream has discussed the relationship between three message attributes and users' perception of credibility (Flanagin and Metzger 2007; Hong 2006; Metzger et al. 2003). The first attribute is message content. Research on message content has attempted to identify which aspects of message content are related to credibility assessment. For instance, quality of a message, currency of a message, and the use of citations in a message are three possible aspects (Rieh and Belkin 1998; Slater and Rouner 1996; Sundar 1998). The second attribute is message organization. Organization-related research has found that the structure of a message can influence credibility assessment. For example, a well written message is more likely to be perceived from credible source than is a poorly written message (Slater and Rouner 1996). Furthermore, message delivery has been related to credibility (Hong 2006). For example, the speed of loading is used to evaluate the credibility of information in a website (Rieh and Belkin 1998).

Although they assess credibility in different ways, credibility researchers have admitted that assessment from either a source or a message perspective is not complete (Wathen and Burkell 2002). It is hard to differentiate the impact of source from the impact of message on the perception of credibility. In other words, credible sources are assumed to create more credible messages; credible messages are assumed to be originated from credible sources (Fragale and Heath 2004). Therefore, source-oriented and message-oriented credibility may have many overlaps. For instance, the notion of reputed credibility in source-oriented studies is similar to the use of citations in message-oriented studies.

Information technology increases the credibility of an argument. One way to increase the reputed credibility of an argument is the use of a source reference. In other words, referring to a reference is similar to increasing the reputed credibility of an argument. Therefore, referring to information technologies can enhance the perception of the credibility of an argument. This implies that information technologies could play a role for persuasion in group decision making setting.

3.3 Hypothesis Development

Past studies have suggested that two group processes, persuasive argumentation and social comparison, can be used to explain why group polarization occurs (Isenberg 1986). Persuasive argument theory has argued that exchanging factual information and data causes people to shift their initial decisions in an extreme direction, whereas social comparison theory has claimed that sharing individual preferences and values leads people to change their original choices. Therefore, persuasive argumentation and social comparison are named as informational influence and normative influence, respectively.

The amount of the use of different types of influence is determined by the nature of the task (El-Shinnawy and Vinze 1998; Kaplan and Miller 1987). Laughlin and his colleagues have proposed that tasks vary along an intellective-judgmental continuum (Laughlin 1980; Laughlin and Earley 1982). That is, for example, if a task is relatively closer to the intellective end of the continuum, its intellective component would predominate over its judgmental component. A task with a predominant intellective component can be completed by focusing on exchanging factual information. This implies that informational influence arguments would be used relatively more than normative influence arguments for intellective tasks. Conversely, a task with a predominant judgmental component can be fulfilled by focusing on sharing individual preferences. This implies that normative influence arguments would be used more, relative to informational influence arguments for judgmental tasks. Thus, to effectively complete a task, group members have to consider the relative use of informational influence arguments versus normative influence arguments because a task involves these two components.

In our study, we did not attempt to compare the effect of informational influence to that of normative influence since past research has demonstrated the result (e.g., Isenberg, 1986). We also did not examine whether the combination of informational influence and normative influence would lead to greater group polarization. However, unlike past studies, our study has focused on how the relative use of informational influence versus normative influence is affected by antecedents and leads to group polarization.

3.3.1 Pre-discussion Individual Decisions and Relative Influence Use

One of the purposes of using teams, rather than individuals, is to bring multiple perspectives to bear on important decisions (Hackman and Morris 1975). Virtual teams further enhance the range of perspectives by bringing together individuals from different organizations and locations (Martins et al. 2004). In some cases, these different perspectives lead to similar conclusions; in others, differences in the ways in which individuals interpret and combine data can lead to very different predictions (Priem et al.

1995). That is, the heterogeneity of pre-discussion individual decisions may be quite different.

A level of heterogeneity could determine how group members complete their tasks. A higher level of heterogeneity indicates that the range of group members' opinions is wider. To complete a task with high heterogeneity, group members are more likely to follow a collective decision. Such following behaviors can intensify, protect, or rebuild their self-esteem (Cialdini and Goldstein 2004) and also can share the risk of making an erroneous decision. Moreover, an increase in heterogeneity makes a task's judgmental component salient, especially during time-constrained discussion. The salience leads group members to pay more attention to social comparison than persuasive argumentation since a group decision will be determined by the consensus of preference (El-Shinnawy and Vinze 1998; Kaplan and Miller 1987). Therefore, the increased likelihood of following behaviors and increased attention to social comparison cause group members to focus on a group process which can facilitate consensus development (i.e., normative influence), rather than a process which can help increase understanding of a task (i.e., informational influence). That is, we can expect that when heterogeneity is higher, group members will use more normative influence relative to informational influence. This suggests that:

> *HYPOTHESIS 1 (H1): Higher heterogeneity of pre-discussion individual decisions is associated with lower relative use of informational influence versus normative influence.*

3.3.2 Task Uncertainty and Relative Influence Use

Research on interpersonal communications (Carlson and Zmud 1999; Daft and Lengel 1984) suggests that uncertainty reduction is one important objective. Uncertainty refers to the gap between the amount of information required to perform a task and the amount of information the performer has (Daft et al. 1987). A high level of uncertainty indicates a large information gap. To effectively accomplish a highly uncertain task, group members tend to focus on a group process which enhances information sharing (i.e., informational influence) rather than a group process which facilitates consensus building (i.e., normative influence). That is, uncertainty could be reduced by gathering more factual information. Thus, it is reasonable to expect that when the level of uncertainty is higher, group members will increase informational influence relative to normative influence.

HYPOTHESIS 2 (H2): Higher task uncertainty is associated with higher relative use of informational influence versus normative influence.

3.3.3 Relative Influence Use and Group Polarization

Group polarization can be explained by informational influence and normative influence. Proponents of persuasive argument theory have argued that group members' positions can be affected by the number and persuasiveness of available arguments during a group discussion. Supporters of social comparison theory, on the other hand, have claimed that group members are motivated to act in a socially desirable direction. To thoroughly investigate group polarization, researchers have suggested that considering two influences simultaneously is more appropriate (Isenberg 1986; Sia et al. 2002).

The relative use of informational influence versus normative influence can determine the extent to which group members polarize the group's decision. As discussed earlier, a meta-analysis has found that the impact of informational influence on group polarization is larger than that of normative influence (Isenberg 1986). This finding suggests that a higher level of relative use will lead to a greater magnitude of group polarization; a lower level of relative use will cause a smaller magnitude of group polarization. A higher level of relative use indicates that, during a group discussion, group members are exposed to relatively more persuasive argumentation than social comparison. Thus, the relative use of informational influence versus normative influence is likely to be positively associated with the magnitude of group polarization.

HYPOTHESIS 3 (H3): The greater the group's relative use of informational influence versus normative influence, the greater the magnitude of group polarization.

3.3.4 Information Technology Reference and Group Polarization

Information technologies can be tools for persuasion (Fogg 2003; Tseng and Fogg 1999). Such tools are used to change people's attitudes and behaviors by increasing the credibility of information received. Fogg and his colleagues have identified four types of credibility. One of those is reputed credibility. Reputed credibility can be increased by using citations, references, or labels. Hence, information with a reference is more believable and persuasive than information without any reference. For instance, referring to a technology such as "NAM" model may increase the persuasiveness of an argument about the patterns of sea level pressure.

The intensity of references determines the persuasiveness of arguments and information. During a time-constrained discussion, group members have to make a group decision as soon as possible. Thus, group members are less likely to exchange messages with many references. That is, the low intensity of references in messages can be expected. In our setting, the members of a virtual team can choose whether they want to cite an information technology to support their arguments. Citing fewer information technologies equals the lower intensity of information technology references. However, the lower the intensity of information technology references, the weaker the persuasiveness of messages. Conversely, the higher the intensity of information technology references, the greater the persuasiveness of messages.

Group members' positions are affected by the persuasiveness of available arguments and messages. The magnitude of group polarization should be even greater when both the relative use of informational influence versus normative influence and the intensity of information technology references are high. When group members are exposed to relatively more informational influence than normative influence, group members are more likely to change their positions in a larger magnitude. This likelihood is amplified in a persuasive environment. During group discussion, persuasiveness can be increased by citing more information technologies.

HYPOTHESIS 4 (H4): The relative use of informational influence versus normative influence and the intensity of information technology reference interact positively in their effect on the magnitude of group polarization, such that the positive effect of the relative use on the magnitude of group polarization is stronger with a higher intensity of information technology reference.

3.4 Method

To evaluate our hypotheses on the relative use of informational influence versus normative influence, we conducted a field study. The field study involved collecting daily data on group discussion content from a virtual smog forecasting team during ground-level ozone season (May 1 to September 30) in Atlanta, Georgia, in 2007 and 2008. The following describes the setting of the data collection and our measures of key variables.

3.4.1 Research Setting

The setting for our study is a ten-person virtual team responsible for forecasting air quality for the Atlanta region. The team is made up of research scientists at a major research university and the state's environmental protection division (EPD). Team members include meteorologists, atmospheric scientists, a geochemist, and an expert in statistics, and are located in various parts of the region.

The primary task of the team each day is to forecast the air quality (i.e., the level of ozone pollutant concentrations measured as parts-per-billion (PPB) in the air) for the subsequent day in the Atlanta metropolitan area and surrounding cities during the ground-level ozone season (May 1 to September 30). The U.S. Environmental Protection Agency (EPA) classifies different levels of air quality into six color zones, based on ozone concentration values. A value between 0-59 (green) is considered "good"; 60-75 (yellow) is "moderate"; 76-95 (orange) means "unhealthy for sensitive groups"; 96-115 (red) is "unhealthy for everyone"; 116-374 (purple) is "very unhealthy for everyone"; and over 374 (brown) is considered "dangerous for everyone," but conditions in this range have never occurred in Georgia. In Atlanta, smog alerts are issued in three color zones: orange, red, and purple. Air quality forecasting is a difficult task, and is particularly challenging in the Atlanta area. For example, thunderstorms can unexpectedly develop and clear out air pollutants, or accidents can trigger major traffic congestion that increases air pollutants. In addition, the smog forecasting team makes predictions for surrounding cities, and a city northwest of Atlanta can experience very different conditions than a city southeast of Atlanta.

This field setting is especially well suited to study the relative use of informational influence versus normative influence by virtual teams. The virtual smog forecasting team consists of an experienced group of experts whose task, predicting the next day's peak ozone concentration, remains constant; however, the heterogeneity of pre-discussion individual decisions and the uncertainty of a task can vary considerably from day to day. In addition, the forecasters use a website to assess information technologies used to make forecasts, to post individual predicted value, and to store team's discussion content. The website allows us to measure team's relative use of informational influence versus normative influence, the intensity of information technology references and predicted air quality level on each day. In sum, studying how an experienced virtual team makes high-uncertainty decisions in a dynamic environment in the same task over time offers a strong test of the extent to which variations in the decision context affect relative use. Moreover, studying such team allows us to investigate how the intensity of information technology references moderates the effect of the relative use on the magnitude of group polarization.

3.4.2 Dependent Variables

Relative Use of Informational Influence versus Normative Influence (*RELATIVE USE*): We selected Sia et al.'s (2002) coding scheme to classify group processes. Past studies provided many coding schemes (El-Shinnawy and Vinze 1998; Huang and Wei 2000; Kaplan and Miller 1987; Sia et al. 2002; Zigurs et al. 1988), but some of these coding schemes have been used in different contexts or for one specific process (e.g., only informational influence process). This study chose Sia et al.'s coding scheme because (1) it was specifically designed to classify group processes as normative influence or informational influence and (2) it can be used to investigate group polarization. Based on Sia et al.'s coding scheme, group discussion was coded into five categories (novel argument, valid argument, pluralistic balance statement, one-upmanship statement, and other statement). The first two types reflected informational influence and the third and fourth types were considered normative influence. The unit of analysis was a sentence which group members uttered during group discussion. Appendix A provides a sample coding.

In order to establish coding reliability, the study included two coders. Coder 1 was one of the authors and Coder 2 was a graduate student who did not know any hypothesis in the study. Before coding forecasting discussions, Coder 1 studied basic meteorology and weather forecasting for a year and frequently discussed coding content with a principle forecaster. We randomly selected 20 of 300 daily discussions for Coder 2: five discussions for 4 conditions (high vs. low heterogeneity and high vs. low task uncertainty). Since weather forecasters used many forecasting jargons (e.g., BL: boundary layer depth; COT: cloud optical thickness) and technology abbreviations (e.g., vis sat: visible satellite imagery), Coder 1 had to interpret such jargons and technology abbreviations to Coder 2 when Coder 2 was coding the discussion content. However, Coder 1 was not allowed to help Coder 2 make any coding decision. Following Kaplan and Miller (1987), we computed the coefficient of agreement for each of the 4 conditions: .84, .89, .90, .96. Overall, the coefficient is .89. Therefore, coding reliability was considered acceptable. Both coders discussed with each other to reconcile their coding differences. After that, Coder 1 independently coded the rest of the discussions.

We measured *RELATIVE USE* by the team on a particular day as the number of informational influence sentences used during the team's chat room discussion that day divided by the number of normative influence sentences used. This ratio controls for potential differences in the number of influence sentences used on a given day. For example, during group discussion, if the team utilizes 10 informational influence sentences and 20 normative influence sentences, the relative use of informational influence versus normative influence on that day is 0.5.

Group Polarization (*POLARIZATION*): Group polarization has been widely considered as a choice shift (Zuber et al. 1992). The choice shift is measured by taking the absolute difference between the final group decision and the average of pre-discussion individual decisions (Sia et al. 2002; Sunstein 2002). The difference refers to the magnitude of group polarization. In other words, a higher value indicates a larger degree of group polarization.

3.4.3 Moderator

Intensity of Information Technology Reference (*INTENSITY*): We measured the intensity of information technology references by dividing the number of information technology references by the number of informational influence sentences used during team discussion. For instance, if the discussion content includes two technology references and ten informational influence sentences, the intensity of information technology reference is 0.2.

3.4.4 Independent Variables

Heterogeneity of Pre-discussion Individual Decisions (*HETERO*): Heterogeneity measures the distribution of group members' pre-discussion decisions (Butler and Crino 1992). Such distribution can be computed by the variance in the initial individual forecasts on a given day. For example, if forecasters made three individual predictions: 75, 80, and 80, the heterogeneity of pre-discussion individual decisions would be 8.33.

Task Uncertainty (*UNCERTAINTY*): Background interviews and discussions after observing the team forecasting process revealed that team members perceived two borders as the most uncertain. The first is the yellow-orange border. A yellow color zone does not involve issuing a smog alert; an orange color zone involves issuing a smog alert for sensitive groups (e.g., children, elders, and individuals with heart or lung disorders.) If the team finds that any air pollutant (e.g., carbon dioxide emission) will impact at least one sensitive group, the team will forecast an orange color zone. Conversely, if the team finds that no air pollutant will affect any sensitive group, the team will forecast a yellow color zone. Thus, the yellow-orange border is seen as uncertain since the team has to obtain additional environmental information to choose between a yellow zone and an orange zone. The second is the orange-red border. A red color zone involves issuing a smog alert for everyone. If the team finds that air pollutants will affect not only all sensitive groups but also everyone else, the team will forecast a red color zone. Otherwise, the team will only forecast an orange color zone if the team finds that at least one group will not be influenced by air pollutants (e.g., young adults with good health conditions.) Thus, the orange-red border is seen as even more uncertain since more information is needed for the team to decide between an orange zone and a red zone. The team did not express similar concerns about predictions at the green-yellow border as this border does not involve a smog alert, so the team did not attempt to identify which color zone is most likely. Accordingly, we used one binary variable to represent uncertainty and coded *UNCERTAINTY* as "1" if the initial team perception was within 5 parts-per-billion (PPB) of the yellow-orange border or the orange-red border; "0" otherwise.

3.4.5 Control Variables

In our analysis, we controlled for other factors likely to affect group processes and group polarization. Prior research has suggested that group size (*GROUP SIZE*) can affect both group processes and group polarization (Butler and Crino 1992; Smith et al. 1994; Teger and Pruitt 1967); thus, we include group size as a covariate. We measured group size for each day by counting the number of forecasters who participated by posting an initial forecast.

In addition, virtual teams can be composed of members from different locations and different expertise. Such differences may make in- and out-group characteristics salient, which would affect group processes (e.g., group cohesion) (Martins et al. 2004). We controlled two basic diversities in virtual teams: expertise and location. First, the virtual smog members' expertise was coded based on their academic training. We classified group members into six categories: "Meteorologist", "Atmospheric Scientist", "Geochemist", "Statistician", "Monitoring Expert", and "Other". Second, the group members were located at either a major research university in Georgia or the state's environmental protection division (EPD). Following past research on team diversity (Knight et al. 1999), expertise diversity as well as location diversity were computed using Blau's (1977) heterogeneity index: $(1- \Sigma p_i^2)$, where p_i is the proportion of the group in the i th category.

Furthermore, to control for differences in ground-level ozone concentrations on weekdays versus weekends (U.S. Environmental Protection Agency 2003), we coded *WEEKDAY* as "1" for Monday to Friday and "0" otherwise. Because ground-level ozone concentrations vary by month and year (e.g., due to the use of reformulated fuel or shifts in population (U.S. Environmental Protection Agency 2003)), we used four binary variables, *JUNE*, *JULY*, *AUGUST*, and *SEPTEMBER*, to distinguish these months from the base month of May.

3.5 Analysis and Results

The data on heterogeneity of pre-discussion individual decisions, task uncertainty, intensity of information technology reference, and the magnitude of group polarization yielded a total of 300 daily observations from 2007-2008. Table 3.1 reports the means, standard deviations, and correlations of the variables in the analysis. As shown in Table

3.1, pair-wise correlations between the variables in our analysis are modest with almost all well below 0.50.

We conducted a number of specification checks. We examined our model for multicollinearity by calculating a condition index for the whole model and variance inflation factors (VIF) for each of the independent variables. As a rule of thumb (Kennedy 2008), a condition index should be lower than 30 and each independent variable should have a VIF < 10 . The condition index and the VIFs were all well below the recommended cutoff value, thus suggesting multicollinearity may not be a potential data analysis problem.

In addition, we conducted Durbin-Watson's test for autocorrelation and White's test for heteroskedasticity (Greene 2003; Kennedy 2008). As for autocorrelation, Durbin-Watson's d-statistic demonstrated that the result of autocorrelation existence was inconclusive. Thus, we conducted a further analysis (see our robustness analysis section). The results showed the autocorrelation was not an issue in our data. As for heteroskedasticity, White's test revealed no diagnostic problem.

Table 3.1: Means, Standard Deviations, and Correlations

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. POLARIZATION	0.26	0.85	1.00													
2. RELATIVE USE	0.54	0.63	0.27	1.00												
3. INTENSITY	0.05	0.14	0.09	0.35	1.00											
4. HETERO	31.49	33.07	0.22	0.26	0.15	1.00										
5. UNCERTAINTY	0.31	0.46	0.19	0.27	0.13	-0.12	1.00									
6. EXPERTISE	0.56	0.15	-0.09	-0.01	0.07	-0.02	0.00	1.00								
7. LOCATION	0.46	0.09	0.04	0.02	0.06	0.07	-0.06	0.23	1.00							
8. WEEKDAY	0.72	0.45	0.00	-0.01	0.06	-0.01	0.02	-0.16	0.15	1.00						
9. JUNE	0.20	0.40	0.00	0.17	0.08	0.18	0.03	-0.40	-0.09	-0.01	1.00					
10. JULY	0.20	0.40	0.01	-0.10	0.12	-0.02	-0.01	0.13	0.02	0.02	-0.25	1.00				
11. AUGUST	0.20	0.40	0.08	0.13	-0.03	-0.06	0.23	0.08	0.07	-0.02	-0.25	-0.25	1.00			
12. SEP	0.20	0.40	-0.07	-0.11	-0.08	-0.04	-0.22	0.09	-0.03	-0.01	-0.24	-0.25	-0.25	1.00		
13. YEAR2008	0.50	0.50	-0.03	-0.14	-0.03	-0.05	0.02	-0.08	0.05	0.00	0.01	-0.02	0.01	0.01	1.00	
14. GROUP SIZE	4.71	1.20	-0.05	-0.07	0.11	-0.03	0.07	0.23	0.41	0.20	-0.13	0.10	0.08	-0.11	0.03	1.00

3.5.1 Relative Use of Informational Influence vs. Normative Influence

The first two hypotheses investigated the relationships between the antecedents of group polarization and the relative use of informational influence versus normative influence. Using hierarchical regression analysis, we estimated the effect of the heterogeneity of pre-discussion individual decisions and the effect of task uncertainty on relative use.

$$
\begin{aligned}
RELATIVE\ USE \\
&= \beta_0 + \beta_1\, WEEKDAY + \beta_2\, JUNE + \beta_3\, JULY + \beta_4\, AUGUST \\
&+ \beta_5\, SEPTEMBER + \beta_6\, YEAR2008 + \beta_7\, GROUP\ SIZE \\
&+ \beta_8\, EXPERTISE + \beta_9\, LOCATION + \beta_{10}\, HETERO \\
&+ \beta_{11}\, UNCERTAINTY + \varepsilon \qquad (\mathbf{1})
\end{aligned}
$$

Table 3.2 displays the results of these estimates. In the first step of our estimation, we entered all control variables into the model. In the second step, adding HETERO and UNCERTAINTY resulted in a significant increase in variance explained ($\Delta R^2 = 0.12$, $F = 22.67$, $p < 0.001$), suggesting that these antecedent variables explain significant variation in the relative use of informational influence versus normative influence.

Hypothesis 1 posited that higher levels of heterogeneity of pre-discussion individual decisions were associated with lower relative use of informational influence versus normative influence. We found that the effect of heterogeneity on relative use was significant, but the sign of the coefficient was in a direction opposite from our expectation ($\beta_{10} = 0.01$, p < 0.01).

Hypothesis 2 postulated that higher levels of task uncertainty were associated with greater relative use of informational influence versus normative influence. The effect of task uncertainty on relative use was positive and significant (β_{11} = 0.38, p < 0.001). Therefore, Hypothesis 2 was supported.

3.5.2 Impact on Group Polarization

Following a standard practice for analyzing models with interaction effects (Aiken and West 1991; Cohen and Cohen 1983), We used hierarchical OLS regression analysis to estimate the effects of the relative use of informational influence versus normative influence as well as the intensity of information technology references on the magnitude of group polarization as shown in Equation 2 below. This approach allows us to evaluate whether the variables add significant explanatory power to the model incrementally over all other variables. As can be seen in the Table 3.3, we first added only the control variables. We then added relative use and the intensity of information technology references into the regression model, which increased the explanatory power of the regression model ($\Delta R^2 = 0.03$, $F = 4.35$, $p < 0.05$), suggesting that relative use and intensity help explain significant variance in the magnitude of group polarization. Finally, we entered the interaction effect between relative use and the intensity of information technology references into the model, which further increased the predictive power of the regression model ($\Delta R^2 = 0.01$, $F = 3.88$, $p < 0.05$), suggesting that the interaction variable explains significant variation in the magnitude of group polarization over that explained by the other variables.

$$
\begin{aligned}
GROUP\ POLARIZATION \\
&= \beta_0 + \beta_1\, WEEKDAY + \beta_2\, JUNE + \beta_3\, JULY + \beta_4\, AUGUST \\
&+ \beta_5\, SEPTEMBER + \beta_6\, YEAR2008 + \beta_7\, GROUP\ SIZE \\
&+ \beta_8\, EXPERTISE + \beta_9\, LOCATION + \beta_{10}\, HETERO \\
&+ \beta_{11}\, UNCERTAINTY + \beta_{12}\, RELATIVE\ USE + \beta_{13} INTENSITY \\
&+ \beta_{14}\, RELATIVE\ USE * INTENSITY + \varepsilon \qquad (\mathbf{2})
\end{aligned}
$$

To evaluate our third hypothesis, we followed the standard statistical procedure (e.g., Greene (2003)) to test main effects in the full model. This requires differentiating Equation 2 with respect to the particular effect and then substituting the mean value of the interacting effect. To test Hypothesis 3, that the relative use of informational influence versus normative influence is associated with the magnitude of group polarization, this is *GROUP POLARIZATION* = ∂*GROUP POLARIZATION* / ∂*RELATIVE USE* = β_{12} + β_{14} * *INTENSITY* = 0.36 + (−0.72)*0.05 = 0.32. Following Greene (2003) the standard error for the coefficient is 0.08, yielding a *t* value of 4.00, $p <$ 0.001. Thus, we find a significant positive relationship between relative use and the magnitude of group polarization, and Hypothesis 3 was supported.

Hypothesis 4 posited a moderating relationship between relative use and the intensity of information technology references on the magnitude of group polarization, such that at higher levels of relative use, the higher intensity of information technology references would be associated with an even greater magnitude of group polarization. As can be seen in Table 3.3, the interaction effect was significant, but the sign of the coefficient was contrary to our expectations ($\beta_{14} = -0.72$, $p < 0.05$). Our results from hypothesis testing are summarized in Table 3.4.

Table 3.2: Relative Use of Informational Influence versus Normative Influence

	Control Variables Only		+ Main Effects		Cochrane-Orcutt Procedure	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
β0 INTERCEPT	0.41	2.82**	0.22	1.46	0.23	1.52
β1 WEEKDAY	0.02	0.22	0.01	0.11	-0.01	-0.10
β2 JUNE	0.34	3.25**	0.22	2.36*	0.22	2.55*
β3 JULY	-0.03	-0.41	-0.05	-0.75	-0.05	-0.91
β4 AUGUST	0.27	1.99*	0.18	1.28	0.18	1.38
β5 SEP	-0.05	-0.76	0.01	0.09	0.01	0.24
β6 YEAR2008	-0.17	-2.40*	-0.16	-2.57*	-0.17	-3.00**
β7 GROUP SIZE	-0.04	-1.21	-0.05	-1.47	-0.04	-1.26
β8 EXPERT	0.26	1.28	0.16	0.81	0.17	0.80
β9 LOCATION	0.35	1.13	0.40	1.46	0.35	1.29
β10 HETERO			0.01	3.18**	0.01	3.22**
β11 UNCERTAINTY			0.38	4.61**	0.40	5.31**
R^2	0.09		0.21		0.24	
R^2 Change	0.09		0.12			
F Change	2.27*		22.67**		47.22**	

N = 300. ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$.

Table 3.3: Impact on Group Polarization

	Control Variables		+ Main Effects		+ Interactions		Cochrane-Orcutt Procedure	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
β0 INTERCEPT	0.31	0.84	0.25	0.68	0.21	0.55	0.13	0.35
β1 WEEKDAY	-0.04	-0.40	-0.04	-0.42	-0.03	-0.31	-0.03	-0.39
β2 JUNE	-0.21	-1.55	-0.26	-1.98*	-0.27	-2.04*	-0.25	-1.86†
β3 JULY	0.04	0.33	0.06	0.45	0.06	0.46	-0.01	-0.09
β4 AUGUST	0.07	0.53	0.02	0.19	0.02	0.20	0.02	0.14
β5 SEP	-0.04	-0.41	-0.04	-0.42	-0.03	-0.30	-0.05	-0.47
β6 YEAR2008	-0.06	-0.61	-0.02	-0.19	-0.01	-0.09	-0.03	-0.37
β7 GROUP SIZE	-0.06	-1.20	-0.05	-0.94	-0.05	-1.05	-0.03	-0.68
β8 EXPERT	-0.78	-1.38	-0.82	-1.45	-0.80	-1.42	-0.74	-1.31
β9 LOCATION	0.90	1.88†	0.80	1.69†	0.81	1.70†	0.80	1.66†
β10 HETERO	0.01	2.98**	0.01	2.31**	0.01	2.35*	0.00	2.10*
β11 UNCERTAINTY	0.42	3.54**	0.33	3.1**	0.32	3.05**	0.34	3.22**
β12 RELATIVE USE			0.25	3.6**	0.36	4.13**	0.34	4.13**
β13 INTENSITY			-0.05	-0.23	0.47	1.57	0.50	1.62
β14 RELATIVE * USEINTENSITY					-0.72	-1.97*	-0.65	-1.84†
R^2	0.13		0.15		0.16		0.16	
R^2 Change	0.13		0.03		0.01			
F Change	2.82**		4.35*		3.88*		4.30**	

N = 300. ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$.

Table 3.4: Hypothesis Summary

No.	Prediction	Result
1 HETEROGENEITY, RELATIVE USE	–	Opposite
2 UNCERTAINTY, RELATIVE USE	+	Supported
3 RELATIVE USE, GROUP POLARIZATION	+	Supported
4 RELATIVE USE * INTENSITY, GROUP POLARIZATION	+	Opposite

3.6 Robustness Analyses

We conducted a number of analyses to verify the robustness of our results. Given the time series nature of the data, we evaluated whether serial correlation was an issue. Using the Cochrane-Orchutt procedure to correct for potential serial correlation, we re-estimated equations [1] and [2]; these results (shown in Tables 3.2 and 3.3) produce estimates that are consistent with those we obtained from ordinary least squares regression, leading us to conclude the serial correlation is not an issue in our data.

Past research has proposed that experience can affect how groups interact and perform (Boh et al. 2007; Martins et al. 2004). Similar to past research, we measured group experience as the number of forecasts the virtual team had made until that day in that year. After experience was taken into account, the estimates were still consistent with those without considering experience. Therefore, experience may not be an issue in our data.

Following Baron and Kenny (1986), we conducted a mediation test to confirm that relative use mediates the relationships between group polarization and its antecedents. A mediator must meet the following conditions. (1) *HETERO* ($\beta = 0.01$, $p < 0.01$) and *UNCERTAINTY* ($\beta = 0.38$, $p < 0.001$) were positively associated with *RELATIVE USE*. Thus, heterogeneity and task uncertainty met the first condition; (2)

HETERO ($\beta = 0.01$, $p < 0.01$) and *UNCERTAINTY* ($\beta = 0.42$, $p < 0.001$) were significantly related to *POLARIZATION* and, thus, support the second condition; (3) *RELATIVE USE* ($\beta = 0.24$, $p < 0.01$) was positively related to *POLARIZATION* and, thus, support the third condition. Further, results show that, after considering *RELATIVE USE*, the effect of *HETERO* ($\beta = 0.01$, $p < 0.05$) and *UNCERTAINTY* ($\beta = 0.33$, $p < 0.01$) became weaker, although still significant, which suggests partial mediation.

We applied a Sobel test to further confirm the significance of the mediation. Results show that the intervening effects of relative use for heterogeneity ($p < 0.01$) and task uncertainty ($p < 0.01$) were all significant. Therefore, the mediation effects of relative use were supported.

3.7 Discussion and Conclusion

Group polarization is an important aspect of group decision making. Our study attempts to understand group polarization from an influence perspective and a technology perspective. This is important because little is known about how the relative use of informational influence versus normative influence is affected by antecedents and affects the magnitude of group polarization in virtual team settings. In addition, we do not know much about whether virtual teams refer to information technology for persuasion and influence.

An influence perspective is supported by our study. We found that the level of task uncertainty was positively associated with the relative use of informational influence versus normative influence. The finding suggests that when the gap between the amount of information required and the amount of information group members possessed becomes larger, group members increase their use of persuasive argumentation relative to the use of social comparison. Contrary to our expectations, we found that heterogeneity of pre-discussion individual decisions was positively associated with the relative use of informational influence versus normative influence. One possible explanation is that an established team mental model can increase factual information sharing. Members with a history of working together are likely to have their team mental model. Such a model allows team members to predict the resource and information needs of their teammates and facilitates team decision making (Cannon-Bowers et al. 1993; Mathieu et al. 2000). Therefore, when members have very different initial views, they may know which information their teammates may ignore. This suggests that when a range of group members' opinions becomes wider, group members who are in a virtual team and know each other well prefer to use relatively more persuasive argumentation than social comparison during a group discussion. Our research setting was a virtual team whose members had worked together for over 10 years.

Furthermore, we found that relative use had a positive effect on the magnitude of group polarization. This finding suggests that group members can either boost or alleviate group polarization when they know how to strategically use different influences. For example, group members can move their group decision to a more extreme direction by providing more objective facts and less social norm information. In contrast, group members can use more social norm statements than objective facts to reduce the group's tendency to make an extreme decision. Overall, consistent with prior experimental studies (El-Shinnawy and Vinze 1998; Sia et al. 2002), our field study confirmed that virtual team members had a tendency to polarize a team decision following discussion.

Our study also demonstrates the importance of the technology perspective. Contrary to our expectations, we found that the intensity of technology references and the relative use of informational influence versus normative influence are substitutive, not complementary in their effects on group polarization. As Figure 3.1 illustrates, when relative use is lower, the effect of intensity is stronger. Conversely, when relative use is higher, the effect of intensity becomes smaller. Therefore, the figure suggests that the two factors are somewhat substitutable. One possible explanation for this result is that people may not focus on both relative use and intensity simultaneously. Higher levels of relative use provide group members enough factual information to decide the magnitude of group polarization. The facts provided will lead group members to focus on informational influence rather than the intensity of information technology references. Conversely, higher levels of the intensity of information technology references assist group members to invoke more factual information from identified sources. This recall will lead group members to consider more information by themselves, thus leading group members to pay less attention to informational influence.

Motivation is another possible explanation. A level of motivation determines which one of two routes in elaboration likelihood model (ELM) people use more to process messages (Petty and Cacioppo 1986). A high level of motivation leads people to use a central route rather than a peripheral route. The central route indicates that people change their beliefs by carefully scrutinizing communication messages. In contrast, the peripheral route indicates that people do not elaborate messages, but depend on external characteristics of messages (e.g., perceived credibility of the source) to alter their attitudes. However, people may use a mixture of a central route and a peripheral route to process different messages. That is, they use a central route to process some messages and a peripheral route to process other messages. In addition, without strong motivation, some members of a group are likely to have social loafing behaviors (Chidambaram and Tung 2005; Karau and Williams 1993). For example, group members may only process a small portion of messages. Both ELM and social loafing behaviors suggest that people may not put all their effort to process information when making a decision. Therefore, the effect of relative use can be substitutive with the intensity of information technology references.

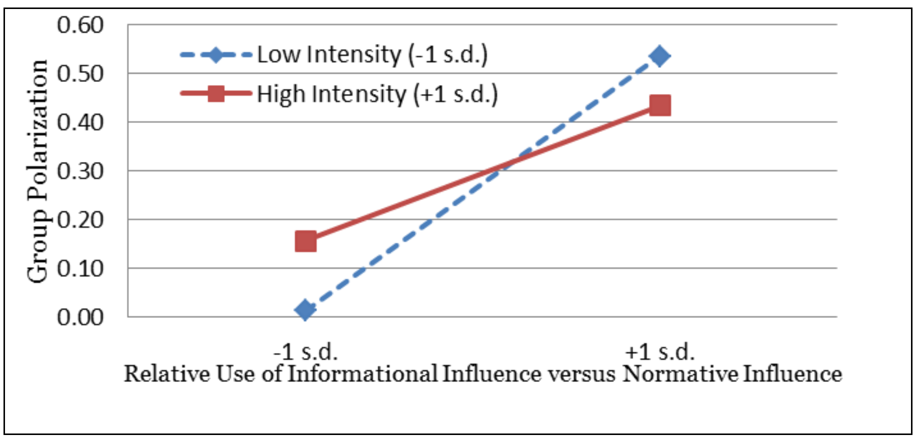


Figure 3.1: Interaction between Relative Use and Intensity

Our study makes two important contributions. First, our study extends the literature on group polarization by hypothesizing and testing an input-process-output framework. Previous studies have investigated the relationships between antecedents and group polarization without including group processes. Moreover, most researchers have argued that applying either an informational influence process or a normative influence process is sufficient to explain group polarization and have treated these underlying processes as a “black box.” Our study opens up this black box and also contributes to the limited number of studies examining both processes together. We introduced the notion of the relative use of informational influence versus normative influence. We found that two important antecedents (i.e., heterogeneity and task uncertainty) determined the magnitude of group polarization through the relative use of informational influence versus normative influence. Such findings validate the argument that relative use is an important process during group discussion.

Our study provides insights into the relative use of informational influence versus normative influence. This relative use is important because decision makers need to know how to increase the magnitude of beneficial group polarization and how to prevent harmful group polarization from becoming worse. As for an increase in benign group polarization (e.g., making more donations to a community that was hit by a natural disaster), our study suggests that decision makers can encourage their group members to use more informational influence relative to normative influence during group discussion. As for prohibition of hurtful group polarization (e.g., keep investing in the failing Enron Corporation), our suggestion is to use less informational influence relative to normative influence.

Second, our study contributes to group polarization research and IS research by theorizing the persuasive role of information technology as a credible source of information. Credibility is believability. The credibility of information can be increased by using labels or references. We introduced the notion of the intensity of information technology references. We found the surprising interaction effect of relative use and intensity on group polarization. The finding suggests that the benefits of these variables are substitutive and that their joint effects experience diminishing effects as both variables increase. Thus, our study reveals the importance of understanding whether decision makers should increase the intensity of information technology references during a discussion. Decision makers who want to increase the magnitude of group polarization even more should use a lower intensity of technology references when the relative use of informational influence versus normative influence is already high. In addition, this finding represents an important contribution to the literature on information technology usage. Recent research has focused on two roles of information technology: a communication tool (e.g., Daft et al. 1987) and a decision making tool (e.g., Todd and Benbasat 1999). However, our findings suggest that information technology can be a powerful persuasion tool. Especially, information technology can be used to persuade group members when informational influence statements are shared less than normative influence statements during group discussion. Such a persuasive role of information technology should provide GDSS system designers with new ideas about how to design a new GDSS. For instance, GDSS can include one feature which allows group members to cite information and sources easily. Further studies need to be conducted to better understand the role of information technology for persuasion. For instance, technology characteristics (e.g., information amount) may moderate the effect of the relative use of informational influence versus normative influence on group polarization.

CHAPTER 4

INTERACTIVE TECHNOLOGY, EXPERTISE, AND GROUP DECISION MAKING

4.1 Introduction

The benefits of decision-making groups are evident in organizations. Groups are very popular at all levels of organizations, such as top management groups, R&D groups, and customer service groups. One of critical decision tasks that groups perform to create significant value is forecasting. Forecasting involves predicting the possible future outcomes of organization decisions. Based on forecasts, organizations are able to allocate valuable and limited resources to meet future business growth in advance. For example, a top management group can predict whether a new innovative product is likely to be successful before the group invests enormous resources into the project. Another example is an R&D group. The group can decide how much budget and how many members it requires to finish a project before the organization allocates resources into different projects. These examples illustrate the importance of a group's ability to effectively forecast.

Accuracy and confidence of forecasting are two critical but distinct outcomes of groups' decision making (Sniezek and Henry 1989; Tsai et al. 2008). In this study, we focus on the confidence of forecasting. Without enough confidence, groups may lose their opportunities to make a good decision. For instance, venture capital teams with low confidence are likely to miss the best time to invest in startup companies (e.g., eBay in 1995, Twitter in 2006, Instagram in 2010) before startup companies are well known and before startup companies' profits start to take off. However, too high confidence may not always be beneficial for groups. For instance, The Economist reported that the top management group in Kodak Corporation was over confident about Kodak's marketing and brand, so the group resisted developing in-house expertise in the new business. This resistance indirectly led Kodak to file bankruptcy. Therefore, understanding which and how factors influence the confidence of group judgment and decision making is extremely important.

Group judgment and decision making depend on various factors, such as technology usage (e.g., Zigurs and Buckland 1998), team composition (e.g., Kayworth and Leidner 2000), task characteristics (e.g., El-Shinnawy and Vinze 1998), and decision rules (e.g., Sniezek 1989). Our study focuses on the first two factors because decision confidence is especially related to information processing (Sniezek and Henry 1989; Tsai et al. 2008). To process a large amount of information efficiently and effectively, a group has to utilize an appropriate information technology and include suitable members. Information technologies have different impacts on group judgment and decision making. Previous studies have focused on communication media/technologies. Based on their goals, group members can select a specific type of communication media to accomplish their tasks. For instance, if group members want to increase the amount of information considered during discussion, group members can adopt computer-mediated communication rather than face-to-face communication (Huang and Wei 2000; Sia et al. 2002). However, in addition to communication media/technologies, decision support technologies are also very important. Because of technical advances, interactive technologies for decision support (e.g., *Gapminder world*) allow the users to interact with data easily and efficiently. Thus, this interactivity may have a significant effect on group judgment and decision-making.

Moreover, team composition is relevant to group judgment and decision making. Team diversity is one of most important dimensions of team composition. Researchers have found that several types of team diversity influenced decision-making processes and outcomes, such as expertise, tenure, and national diversity (Dahlin et al. 2005; Kilduff et al. 2000; Knight et al. 1999). However, Van der Vegt et al. (2006) has proposed another important type of team diversity and has called it "expertness diversity", which refers to the differences in the level of expertise/domain-specific knowledge between groups. Groups with different levels of domain-specific knowledge may have different decision-making processes and outcomes.

Although the literature discusses the impacts on group decision making of information technology and of team composition separately, there is relatively little knowledge of how these two factors together affect group outcomes, especially decision confidence. Prior studies have found that the amount of information was associated with the level of decision confidence (Budescu and Rantilla 2000; Oskamp 1965; Tsai et al. 2008). The present study investigates how technologies with the same amount of information but the different levels of interactivity affect decision confidence. In addition, previous studies have focused on how the level of domain knowledge (i.e., experts vs. novices) influences individual decision making (Ericsson and Lehmann 1996; Sonnentag 1998). This study focuses on the level of domain knowledge at the group level. Specifically, we examine how group domain knowledge moderates the effect of technology interactivity on decision confidence. Furthermore, to extend prior research, this study focuses on the magnitude of a shift in decision confidence rather than the level of decision confidence. Therefore, the present study is an attempt to understand how the impacts of these two factors can increase group leaders' ability to adjust decision confidence.

The rest of this paper is organized as follows: The next section reviews the relevant literature, followed by a hypothesis development section. The research method is then described, and the results of data analysis are reported. The final section includes the discussion of the finding, the implications for theory and practice, and the suggestions for future research.

4.2 Literature Review

4.2.1 Interactivity

Interactivity has a variety of definitions because it has been investigated by many academic disciplines, such as Communication (e.g., Rafaeli and Sudweeks 1997), Education (e.g., Smith et al. 2005), Marketing (e.g., Ariely 2000), and Human-computer interaction (e.g., Teo et al. 2003). Because these disciplines have their own goals and perspectives, there are field-specific definitions of interactivity as well as different focused dimensions of interactivity (Lowry et al. 2009). Some disciplines (e.g., Communication) have considered interactivity as a process of message exchange, while others (e.g., Human-computer interaction) have viewed interactivity as the presence or absence of particular features of a medium/technology (McMillan and Hwang 2002). Although these disciplines have investigated the notion of interactivity differently, interactivity is normally considered to include three dimensions (Liu 2003; Song and

Zinkhan 2008): active control, two-way communication, and synchronicity. Active control refers to the extent to which users are able to control information content. Two-way communication refers to the extent to which the medium/technology enables communication between two or more entities. Synchronicity refers to the extent to which members' input into a communication and the response they receive from the communication are simultaneous.

4.2.2 Interactive Technology Use

Groups can benefit from interactivity provided by information technology. Previous studies have demonstrated that interactive technologies can facilitate information processing (Jiang and Benbasat 2007), fulfill communicating members' needs (Lowry et al. 2009), build a shared interpretive context (Zack 1993), reduce decision effort (Wang and Benbasat 2009), and enhance decision performance (Tan et al. 2010). Information processing and communication needs are especially salient for group decision-making processes. Our study focuses on these two aspects. People can use interactive technology to facilitate information processing. Technological interactivity enhances the users' ability to explore information (Ariely 2000; Lurie and Mason 2007). That is, technologies with interactive features enable the users to exercise great discretion in the presentation of complicated information structures and hidden information patterns. Moreover, Jiang and Benbasat (2004) have demonstrated that a technology with interactive features is likely to increase users' cognitive belief that the technology can help the users evaluate their decision contexts (e.g., shopping for products).

In addition to the facilitation of information processing, interactive technologies are also likely to fulfill members' dynamic needs for information. During interpersonal communication, members' needs for information may change frequently (Ariely 2000; Beach 1993). Specifically, after acquiring new information, group members may update their hypotheses and thinking. These updates may spark new information needs, and resolving individual differences becomes difficult. However, the difficulty can be mitigated by interactive technology because interactive technology allows group members to tailor information based on their needs, interests, or decision context (Fogg 2003).

4.2.3 Expertise/Domain-specific Knowledge

Research on expertise has investigated in different views and in various contexts. Prior studies have focused on two views. Sociologists tend to view experts as people who obtain socially recognized titles (e.g., Dr.) or certificates (e.g., CPA)(Dane 2010). Psychologists tend to view experts as people who have a high level of domain-specific knowledge acquired through experience, learning, or practicing (Chi 2006; Chi et al. 1981; Chi et al. 1982). In addition, previous studies have investigated the effect of expertise in many contexts, such as chess (Chase and Simon 1973), medicine (Patel and Groen 1991), physics (Chi et al. 1981), forecasting (Stewart et al. 1992), auditing (Bédard 1989), programming (Sonnentag 1998), and sports (Devine and Kozlowski 1995).

In this study, the psychologists' view of expertise is selected because the level of domain-specific knowledge is more relevant to information processing and decision making. Research on expertise in psychology has shown that experts (i.e., high domain knowledge people) differ from novices (i.e., low domain knowledge people) in the structure of their domain-specific knowledge (Bédard and Chi 1992; Dane 2010; Mitchell and Dacin 1996). Knowledge structure is determined by the amount of concept components and the relationships among those components. Therefore, an expert's knowledge structure includes a larger quantity of concept components than does a novice's knowledge structure. In addition, the amount of interrelationships among components tends to be greater in an expert's knowledge structure than in a novice's knowledge structure.

The differences between experts' knowledge structure and novices' knowledge structure affect information-processing activities. Experts can process and consider more information because experts have a greater ability to put information in chunks (Mackay and Elam 1992). Experts can also recall organized patterns easily since they create associative relationships between information components (Mackay and Elam 1992). In addition, Shanteau (1992) have found that experts differ from novices in what information is used. Specifically, experts are more likely to select relevant information to make a decision than are novices. For instance, experienced auditors are more likely to know which information is irrelevant than are inexperienced auditors. Furthermore, experts are more likely to identify and detect patterns than are novices. For instance, expert radiologists who view X-ray film can identify more patterns in X-ray films than can novice radiologists (Chi 2006; Lesgold et al. 1988).

The differences also affect decision outcomes. Because their knowledge structure, experts can detect more information patterns, consider more relevant information, and process more information than can novices. This superior ability leads experts to generate better solutions (Bédard and Chi 1992). That is, on average, experts outperform novices. Moreover, previous studies have found that the amount of information processed is positively related to the level of confidence (Budescu and Rantilla 2000; Tsai et al. 2008). Because experts have a higher ability to process a large amount of information than do novices, experts tend to be more confident in their decisions than do novices. Therefore, the level of domain-specific knowledge determines decision accuracy as well as decision confidence.

4.3 Hypothesis Development

Members of a group share diverse information to persuade other members and then reach a decision consensus. Previous studies on group decision making have proposed that a choice/decision shift is the outcome of consensus development (Isenberg 1986; Myers and Lamm 1976). In this study, we are interested in two factors which are relevant to consensus development and information processing: the use of technology and the composition of a group. In addition, we are interested in a shift in decision confidence. Although a shift in decision confidence could either increase or decrease, we focus on an increase in decision confidence here because information technology is generally assumed to help group decision making.

4.3.1 Interactive Technology and Group Decision-making

By using an interactive technology, a group is likely to increase its decision confidence following group discussion. An increase in confidence results from two benefits of interactive technology. First, interactive technology facilitates information processing. By providing many technology features, interactive technology allows users to integrate and consider more information efficiently. For instance, *Gapminder World*, one example of interactive technology, includes a "select" feature to let its users deliberate several types of information simultaneously. In addition to information integration, interactive technology also helps the users discover more patterns and insights which may not be identified easily (Lurie and Mason 2007). Some of these patterns and insights are very likely to be novel information to other users. This benefit of interactive technology allows members of a group to not only consider more information but also identify more novel information during discussion. Previous studies on group decision making have shown that members of a group are more likely to shift their decisions or confidence levels when the amount of information and the novelty of information increase (Isenberg 1986; Myers and Lamm 1976; Sia et al. 2002). Therefore, the use of interactive technology is likely related to an increase in confidence level.

The second benefit of interactive technology is its superior ability to control information. When making a group decision, members may have diverse needs for information and may also change their needs frequently during discussion. The dynamic needs are more likely to be fulfilled if people increase their ability to control information (Ariely 2000). Information technology can enhance this ability by interactive features. For instance, a "filter" feature lets people to decide which information they want to consider and an "abstract" feature lets people to decide how detail information is presented. Because of interactive features, information technology allows members of a group to provide the other members with more tailored information based on the other members' needs for information. The tailored information can fulfill members' dynamic needs more, so members are more confident in their decision (Ariely 2000). In addition, such tailored information is more persuasive than non-tailored information (Fogg 2003). Previous studies have found that people are more likely to shift their decisions when receiving persuasive information during discussion (Isenberg 1986). Therefore, members of a group are likely to increase decision confidence when using an interactive technology. These two benefits lead us to hypothesize that:

> *H1: Groups using a technology with a high level of interactivity increase their confidence following discussion more than do groups using a technology with a low level of interactivity.*

4.3.2 Domain Knowledge, Interactive Technology, and Group Decision-making

The level of domain knowledge is one characteristic that can affect information processing activities. As noted earlier, people with a high level of knowledge in their domain (i.e., experts) tend to store information in chunks. These chunks allow experts to process and consider more information than people with a relatively low level of domain knowledge (i.e., novices) (Bédard and Chi 1992; Mackay and Elam 1992). Moreover, when the level of domain knowledge increases, the ability to find relevant information, recognize missing information, and create associations between information increases (Chi 2006; Shanteau 1992). In this study, we consider a group with a high level of expertise as a group where the majority of members possess high domain knowledge. We call it an expert group. In contrast, a novice group is a group where the majority of members possess low domain knowledge. An expert group has a greater ability to identify relevant information, consider more information, and recognize information patterns easily than does a low expertise group. Therefore, the knowledge structure of an expert group is significantly different from the knowledge structure of a novice group.

The nature of knowledge structure influences how an interactive technology is used. Due to technological advances, information technology can provide users with a large amount of technology features to interact with data (e.g., filter, link, encode, explore, and recognize). Although interactive features do help process information efficiently, users may not utilize a number of interactive features provided by a technology. Expert groups are likely to use many interactive features to make a decision because their knowledge structure is composed of numerous relevant information components and sophisticated relationships between information components. In contrast, novice or less expert groups are likely to utilize fewer interactive features because these groups know little about which information components are relevant and how these components are linked.

The nature of knowledge structure also affects benefits obtained from the use of interactive technology. Experts have a greater capacity to process information, and interactive technologies provide a better platform to present and view information. In addition, previous research has found that, when users' level of domain knowledge increases, users are more likely to leverage an information technology which is designed for their domains (Lee et al. 2008; Wu and Lin 2006). Therefore, the level of domain knowledge should complement interactive technology. In other words, members of an expert group are able to understand how to use interactive technologies to facilitate information processing and fulfill the other members' information needs more than are members of a novice group.

The effect of interactive technology on group confidence depends on the level of domain knowledge/expertise. As argued in H1, the positive effect depends on the amount of information considered and the novelty of information. In addition, because of the nature of knowledge structure, expert groups use more interactive features and obtain more the benefits of interactive technology than do novice groups. Therefore, expert groups are able to consider information and identify patterns even more by using a technology with a high level of interactivity than a technology with a low level of interactivity. Conversely, since novice groups cannot leverage the benefits of interactive technology, a technology with a high level of interactivity and a technology with a low level of interactivity may be not different for novice groups in terms of the amount of information considered and the amount of novel patterns identified. This suggests that:

H2: Level of group domain knowledge moderates the relationship between the use of interactive technology and an increase in group decision confidence.

4.4 Method

4.4.1 Experiment Design

To examine our research model and hypotheses, we conducted a laboratory experiment in which we manipulated the level of interactivity in technologies (high interactive vs. low interactive) in two different levels of domain knowledge groups (high domain knowledge vs. low domain knowledge). A between-subject experimental design was employed. We selected a football forecasting task which has been used in numerous laboratory studies (Riggs 1983; Sanna and Schwarz 2003; Simmons et al. 2011; Tsai et al. 2008).

4.4.2 Participants

The 218 undergraduate students at a large southeastern U.S. university were drawn from a core business course and received course credit for participating. The mean age of the participants was 21 years, and 47% were female. The participants were assigned to the four experimental treatments. We used a 3 and 4-person team as the unit of analysis. Therefore, we had total of 53 teams[1]: 13 teams in the LowInteractivity-LowExpertise condition, 14 teams in the LowInteractivity-HighExpertise condition, 13 teams in HighInteractivity-LowExpertise condition, and 13 teams in HighInteractivity-HighExpertise condition.

4.4.3 Experimental Procedure

The experimental procedures were as follows. Upon arrival at the laboratory, participants were assigned to teams based on their level of domain expertise in football (as described in a following section) and the teams were randomly assigned to use either a high interactive technology or low interactive technology. Participants were also told that the goal of the study was to understand how decision making teams forecast the outcome of a college football game. They were required to make both individual and team predictions.

Prior to their first individual predictions, the participants were trained to use an interactive technology assigned. An experimenter explained how to use the technology

[1] Of the 53 teams, there were 43 4-person teams, and 10 3-person teams. The 3 person teams were distributed among the conditions roughly evenly.

and answered any questions about the technology. The training was to make sure participants would know how to use their assigned technology. After the training, participants were asked to forecast the winner of a college football game between two traditional rivals (TEAM A or TEAM B) and to estimate the chance that their choice was correct (%). In the meanwhile, the participants were told that group discussion was prohibited.

After all participants finished individual predictions, the experimenter told the participants to do their group predictions. A group prediction task was the same as an individual prediction task. The participants in a group had to reach one consensus about their group forecast. Group discussion was encouraged.

After finishing group predictions, the participants completed a computer-based survey asking for demographic information, computer ability, and so on. Once surveys were finished, participants were allowed to leave.

4.4.4 Manipulation of Independent Variables

4.4.4.1. Interactive Technology

Two experimental technologies (high interactive vs. low interactive) were used in the study. The interactive level of a technology decided the extent to which the technology afforded the users to interact with data (Ariely 2000). Our high interactive technology was similar to Gapminder World (http://www.gapminder.org/). This well-known technology can facilitate information processing and pattern finding because it provides users with many interactive features. Based on Yi et al. (2007a), our high interactive technology included 4 interactive features: filter, encode, abstract, and tag. A filter feature allows users to select specific data based on their needs. For instance, participants can control which football team statistics they want to consider. An encode feature permits users to see data using different representations. For example, participants can change a bar chart to a trend chart. An abstract feature allows users to see data in more or less detail. For instance, participants can see an overview of data using zoom-out and see the detailed view of data using zoom-in. A tag feature permits users to mark specific data items. For example, to easily keep track of data items of interest, participants can tag these items. Therefore, the participants of a high interactive technology can interact with data in any way they wanted. The other technology was called a low interactive technology. The participants using a low interactive technology were only allowed to select different data to present in the screen. That is, a low interactive technology only included a filter feature. These two experimental technologies included identical data, but they varied in interactivity level. The appendix provides a screen shot of the high interactive technology and of the low interactive technology used in the experiment.

4.4.4.2 Online Questionnaire

Since our experimental task was related to forecasting outcomes in a football game, we had to find most relevant football statistics which should be presented in our experimental technologies. By using Amazon Mechanical Turk, we invited 93 people who were familiar with football to do our online questionnaire. Based on their responses, we included 13 football statistics, such as points, points allowed, passing efficiency, rushing defense, and turnover margin. To make our experimental task challenging, we selected two college football teams which competed against each other once per year and had each won 3 out of the last 6 games (years 2005 to 2010). We collected 13 team statistics of these two teams. Participants only knew pseudonyms (TEAM A vs. TEAM B) instead of the real names of the teams. The use of TEAM A and TEAM B labels can control for participants' idiosyncratic knowledge about particular teams or games beyond what was provided in the experiment (Tsai et al. 2008). We asked the participants whether they could identify the real team names from the team statistics, but none of the participants in the study could do that.

4.4.4.3 Level of Expertise

We categorized each participant as either a high football knowledge person or a low football knowledge person, based on the participants' scores in a football knowledge pre-survey. The survey had 3 assessments of football domain knowledge. The first assessment objectively tested participants' football knowledge by using 10 football questions. We used similar football questions as in Tsai et al. (2008). In the second assessment, participants were asked to self-rate their knowledge of football. In the third assessment, the participants were asked to rate how closely they followed the football season. The last two types of assessment were used in several prior studies (Sanna and Schwarz 2003; Simmons et al. 2011). Using the three assessments, we conducted a cluster analysis (k = 2) to break our sample into two categories: a high football knowledge person and a low football knowledge person.

According to this categorization, the participants were assigned to either an expert team or a novice team. We called a group with all high football knowledge people as a football expert team and a group with all low football knowledge people as a football novice team.

4.4.5 Measures

4.4.5.1 Dependent Variable

As described earlier, participants were asked to choose the winner of a college football game between two traditional rivals (TEAM A or TEAM B) and to estimate the confidence of their choice was correct (%) before group discussion. Then, participants were asked to make a group prediction, which is the same as pre-discussion individual prediction.

Our dependent variable was a shift in group confidence. This variable can represent the magnitude of change in group confidence following group discussion. A shift was measured by taking the difference between the final group confidence level (%) and the average of pre-discussion individual confidence levels (%)[2] (Sia et al. 2002; Sunstein 2002; Zuber et al. 1992). A positive value of a shift indicates that a group increases its decision confidence following discussion, whereas a negative value of a shift reflects that a group reduces its decision confidence following discussion.

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[2] Pre-discussion individual confidence was revised when a pre-discussion individual decision and a final group decision were different. We considered the difference between 100% and pre-discussion individual confidence as a revised individual confidence. For example, group member 1 chose TEAM A with 60% confidence and her group chose TEAM B, a revised pre-discussion individual confidence was 40% (i.e., 100% - 60%).

4.4.5.2 Control Variables

Perceived usefulness and perceived ease of use of technology are two important variables that can influence how groups use information technology to make a football prediction. To minimize the influence, perceived usefulness and perceived ease of use were measured using items from Venkatesh and Davis (2000). These two control variables were used as covariates in the analysis.

4.4.6 Experimental Manipulation Checks

4.4.6.1 Interactivity Check

We verified whether the two experimental technologies (high interactive vs. low interactive) were different in interactivity level. We adopted both objective and subjective measures of interactivity level. First, two experimental technologies varied in the amount of interactive features. After extensively reviewing the features of information technology, Yi et al. (2007a) proposed 7 general interactive features which are widely used in many free and commercial technologies. Based on this study, our high-interactive technology included four interactive features, while the low-interactive technology included only one interactive feature. Second, in our pilot test, we examined the perceived interactivity level of two technologies by using one 5-Likert scale item from Schlosser (2006): "How interactive did you find this technology?" The result indicated that the participants in the high-interactive technology condition reported a significantly higher level of perceived interactivity than those in the low-interactive technology condition (M_{High} = 4.23, M_{Low} = 3.17; $t(74) = 5.86$, $p < 0.0001$). Therefore, the manipulation of different levels of interactivity was successful.

4.4.6.2 Expertise Check

A *t*-test was used to ascertain that expert teams are significantly different from novice teams. As we mentioned previously, we adopted three football-related measures to classify the participants into either a football expert or a football novice. Football experts were assigned to expert teams and football novices were assigned to novice teams. We found that football expert teams were significantly different from football novice teams in terms of the average of members' answers to football questions (M_{Expert} = 8.43, M_{Novice} = 3.37; $t(51) = 22.23$, $p < 0.0001$), the average of members' self-reported knowledge (M_{Expert} = 5.51, M_{Novice} = 2.47; $t(51) = 20.83$, $p < 0.0001$), and the average of members' football closeness of following the football season (M_{Expert} = 5.47, M_{Novice} = 2.16; $t(51) = 18.70$, $p < 0.0001$).

4.5 Data Analysis and Results

4.5.1 Aggregation Analysis

To test our research hypotheses, we used an ANCOVA analysis controlling for two important covariates which are related to technology use: Perceived Ease of Use and Perceived Usefulness.

Before including these two covariates in the analysis, we had to ensure whether the aggregation of individual responses up to the group level was appropriate (Gallivan et al. 2005). We computed a within-group reliability (*Rwg*) to examine whether sufficient convergence existed among participants in each group on these two perception measures

(James et al. 1984). The average *Rwg* scores for perceived ease of use and perceived usefulness were 0.75 and 0.76, respectively. These values indicated that the individual-level data for these covariates could be appropriately aggregated to the group level. We then averaged individual responses and included these averages in the ANCOVA analysis.

We analyzed whether three and four-person groups can be combined. Data analysis indicated that there were no differences for three and four-person groups in three variables: a shift in group confidence, perceived usefulness, and perceived ease of use. Therefore, the data for both group sizes has been combined to examine our two hypotheses.

4.5.2 Hypothesis Tests

The first hypothesis examined the effects of use of interactive technology on a shift in group confidence. The results demonstrated a significant main effect of interactive technology on a shift in group confidence ($F(1,53) = 10.52$, $p < 0.001$). Consistent with our expectation, groups using a technology with a high level of interactivity increased their confidence more ($M_{High} = 14.32\%$) than did groups using a technology with a low level of interactivity ($M_{Low} = 5.17\%$). Therefore, H1 was supported.

The second hypothesis investigated the interaction effect between the use of interactive technology and the level of group domain knowledge on a shift in group confidence. The results demonstrated a significant interaction effect ($F(1,53) = 6.60$, $p < 0.05$). Follow-up comparison tests were used to further investigate interaction effects.

The results revealed that expert groups using a technology with a high level of interactivity significantly increased their confidence more than did expert groups using a technology with a low level of interactivity (M_{High} vs. M_{Low} = 20.52% vs. 4.67%, $p <$ 0.001). In addition, novice teams using a technology with a high level of interactivity were not significantly different from novice teams using a technology with a low level of interactivity in terms of a shift in group confidence (M_{High} vs. M_{Low} = 8.12% vs. 5.68%, p = 0.52). Thus, Hypothesis 2 was supported. Table 4.1 summarizes the results of the ANCOVA and Table 4.2 summarizes marginal means.

Table 4.1: ANCOVA Summary: A Shift in Group Confidence

Source	Sum of Squares	df	Mean Square	F	Sig.
Interactivity	927.81	1	927.81	10.52	.002
Expertise	415.38	1	415.38	4.71	.035
Interactivity * Expertise	581.80	1	581.80	6.60	.013
Perceived Ease of Use	1141.88	1	1141.88	12.95	.001
Perceived Usefulness.	698.22	1	698.22	7.92	.007
Error	4145.04	47	88.19		
Total	11315.64	53			

Table 4.2: Marginal Means and Results of Hypotheses Testing

Expertise	Interactivity	Mean	SD	Hypotheses	*p* value
	High	14.32	1.93	H1: High Interactivity > Low Interactivity	.002
	Low	5.17	1.89		
High	High	20.52	2.76	H2a: High Interactivity * High Expertise > Low interactivity * High Expertise	.000
High	Low	4.67	2.57		
Low	High	8.12	2.64	H2b: High Interactivity * Low Expertise > Low interactivity * Low Expertise	.521
Low	Low	5.68	2.67		

4.6 Discussion and Conclusion

Decision accuracy and decision confidence are two distinct outcomes of decision making. However, there are relatively little theoretical and empirical understandings of decision confidence, especially, at the group level. Research suggests that confidence of group decision making is related to information processing (Boje and Murnighan 1982; Puncochar and Fox 2004; Sniezek 1992). When receiving a large amount of information, people are likely to have a high level of decision confidence. In addition to the amount of information, we know little about whether groups' ability to process information also influences decision confidence. This ability can be affected by technology use and group composition. Moreover, research suggests that information processing determines how groups shift their decisions (Isenberg 1986; Sia et al. 2002). Therefore, in this study, we attempt to understand a shift in group confidence from a technology perspective and a team perspective.

We investigate how technology interactivity affects a shift in a group confidence. Technology interactivity allows users to interact with information easily and efficiently (Lurie and Mason 2007). Because of technical advances, a high interactive technology is able to provide users with many interactive features, such as filter, link, encode, explore, and recognize. We hypothesize that groups using a high interactive technology will increase their decision confidence more than will groups using a non/low interactive technology (Hypothesis 1). Our results suggest that the use of a high interactive technology increases group confidence by 14%, but the use of a low interactive technology increases group confidence by 5%.

We also examine how the level of team domain knowledge influences the relationship between interactive technology and group confidence (Hypothesis 2). Our study demonstrates the importance of the domain knowledge perspective. We find that the effect of technology interactivity on a shift in group confidence depends on the level of group domain knowledge. As Figure 4.1 illustrates, expert groups using a high interactive technology increase their confidence of predicting an accurate outcome more than do expert groups using a low interactive technology. Experts groups increase their confidence by 21% and novice groups increase their confidence by 5% in a high interactive technology condition. However, our findings do not show that novice groups using a high interactive technology increase their confidence of predicting an accurate outcome more than do novice groups using a low interactive technology. Novice groups using a high interactive technology and novice groups using a low interactive technology do not differ in their changes in group confidence (8% vs. 5%). The findings of these two perspectives are consistent with the previous studies which have proposed the positive relationship between a choice shift and the amount of information shared and considered (Burnstein and Vinokur 1977; Sia et al. 2002; Siegel et al. 1986).

Our findings contradict to some studies. Researchers have found that individuals are less confident in their decisions when they consider more alternatives or they think about more pros and cons of each alternative (Cats-Baril and Huber 1987; Koriat et al. 1980). However, previous study has also demonstrated that information sharing is biased in a group setting (Stasser and Titus 1985). During discussion, members of a group are likely to share information which supports their group preference. That is, group members may pay more attention to one alternative and pros of this alternative.

Therefore, the opportunity of reduction in the level of group confidence decreases in a group setting. Our contradictory findings may be the different unit of analysis. Group decision making rather than individual decision making is our focus.

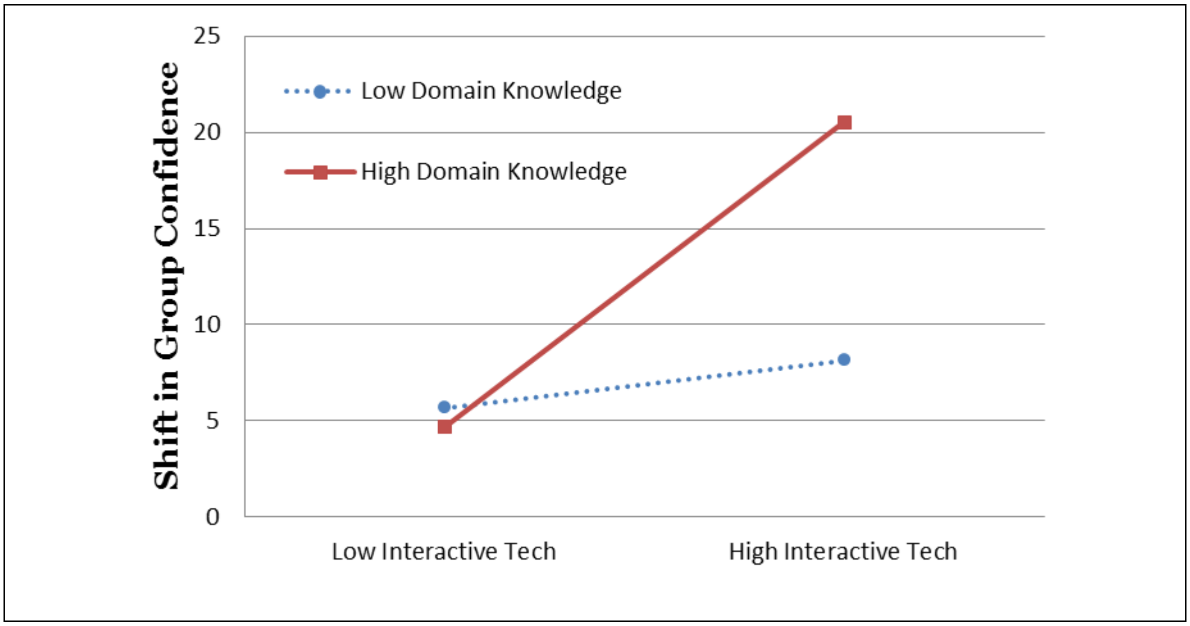

Figure 4.1: Interaction between Technology Interactivity and Domain Knowledge

4.6.1 Theoretical Contribution

Our study makes 2 contributions. First, our study extends the literature on group decision-making by hypothesizing and testing the effects of technology interactivity. Previous studies have focused on how interactive technology influenced individual decision-making processes and outcomes (Häubl and Trifts 2000; Jiang and Benbasat 2007; Tan et al. 2010; Wang and Benbasat 2009). These studies were all at the individual level rather than the group level. In addition, although some prior research has focused on how technology interactivity affected interpersonal communication (Lowry et al. 2009; Zack 1993), this prior research has paid more attention to communication than decision making. Furthermore, previous studies have focused on the level of decision confidence rather than a shift in decision confidence (Sniezek and Henry 1989; Tsai et al. 2008). Therefore, our study contributes by examining the relationships between interactive technology and group decision making. We have found that groups using a high interactive technology can increase their confidence in a forecasting task more than can groups using a low interactive technology. Our findings validate the argument that the use of interactive technology is an important way to increase group confidence.

Second, our study contributes to the literature on information system usage by hypothesizing and testing the moderating effect of domain knowledge. Previous studies have found several important factors which moderated the relationship between technology usage and decision making, including task goals (Schlosser 2003), task characteristics (Jiang et al. 2010), and so on. Our results suggest that group domain knowledge is important, but it cannot always help groups increase their decision confidence. Specifically, group domain knowledge is more beneficial only when groups use a high interactive technology to forecast. In addition, group domain knowledge has no effect when groups use a low interactive technology. Our study demonstrates the importance of level of domain knowledge within a group using a technology with high interactivity.

4.6.2 Practical Contribution

Our study provides insights into technology interactivity at the group level. Predicting a future outcome is complex and difficult, so decision confidence is the first and most important thing. Without enough confidence, groups will hesitate when considering their next step and will be very likely to waste valuable time and resources. Therefore, group decision leaders need to know how to increase group decision confidence, especially, in forecasting tasks. Our study suggests that the use of interactive technology matters. Specifically, on average, groups can increase their decision confidence almost twice as much by using a high interactive technology than by using a low interactive technology.

Our study also reveals the importance of group domain knowledge in group decision making. Although using an interactive technology can increase group confidence, the group can increase group confidence even more when its members possess a high level of domain-specific knowledge. Our results show that, on average, expert groups can increase their group confidence four times more by using a high interactive technology than by using a low interactive technology. However, on average, novice groups are not different in their confidence shift by using either a high interactive technology or a low interactive technology.

Furthermore, our study has implications about the importance of information technology for group decision-making outcomes, especially, decision confidence. Our findings provide designers with new ideas about how to customize decision technologies to fit the characteristics of a group. If members of a group all possess a high level of domain-specific knowledge, system developers can include many interactive features in the system. However, if members of a group possess a relatively low level of domain-specific knowledge, system developers should only include a few but necessary interactive features in the system.

4.6.3 Limitations & Future Research Directions

Our study opens up multiple avenues for future research. One concern of this study could be the appropriateness of selection of methodology and sample. The experiment method and student samples were used because we followed numerous previous studies on a forecasting task (Sanna and Schwarz 2003; Simmons et al. 2011; Tsai et al. 2008). However, it is important for future research to validate our findings by using different methodology and diverse samples.

Second, technology characteristics should be investigated into more detail. Our study considered only one important technology characteristic, interactivity, and its two levels. To maximum the treatment variance, we used one information technologies with a very high level of interactivity and the other technology with a very low level of interactivity. However, we acknowledge that technologies may have various interactive levels, which, in turn, lead to different magnitude of a shift in group confidence. In addition to interactivity characteristic, representation formats have different advantages in decision making (Lurie and Mason 2007). It is possible that visual representation technologies have stronger impacts on a shift in decision confidence than do non-visual representation technologies because visual technologies can provide more information patterns. An important direction for future research is to consider more technology characteristics and their impacts on a shift in group confidence.

Finally, future research can examine other factors that influence the relationship between technology use and group confidence. Our study focused on group domain knowledge since it is relevant to information processing. However, researchers have identified many other factors which can affect information processing, such as motivation, cohesion, and task characteristics (Kanfer and Ackerman 1989; Lim and Benbasat 2000; Yoo and Alavi 2001). Therefore, future research can investigate how other factors determine the effect of technology on group confidence.

CHAPTER 5

CONCLUSION

The purpose of this dissertation is to investigate the new role of information technology. Previous studies examined the role of information technology for decision support and for communication support. Little is known about the role of information technology for persuasion.

In essay 1, I use a filed data to answer two questions. First, under which conditions are decision making groups likely to reference more visual technologies? Second, how does the reference of visual technologies affect decision making? I found that members of a group were likely to increase the reference of visual technologies during discussion when their opinions were diverse and when the consequence of making a wrong decision was high. In addition, referencing more visual technologies can reduce decision bias but not improve decision accuracy. This essay can contribute to the research on consensus development. Specifically, I demonstrated that group members can use visual technologies to persuade the other members and then reach a consensus.

Essay 1 focuses on the relationship between the use of visual technologies and consensus development. However, in my essay 2, I investigate the process by which decision making teams reach a consensus. Three research questions are asked. First, under which conditions are decision making groups likely to adjust group process? Second, how does the adjusted process affect group polarization? Third, how do information technologies affect the process? I found that members of a group were likely to increase their use of informational influence relative to that of normative influence when they had diverse opinions before discussion and when a decision task was uncertain. In addition, relative use of informational influence versus normative influence was positively related to group polarization. Furthermore, the relative use of informational influence versus normative influence and the intensity of technology references were substitutive in their effects on group polarization. Essay 2 can contribute to the research on group polarization by investigating the input-process-output framework. I identified one important mediator: Relative use of informational influence versus normative influence. In addition, I demonstrated that group members can use information technologies to affect group polarization.

The findings of the first two essays motivate me to design an experiment study to further investigate effects of visual technologies on persuasion. In essay 1, I know that information technology can affect a shift in decision. In addition, I know that group members can use visual technologies to persuade the other group members and then reach a consensus. However, I did not know why visual technologies can be used to persuade group members and reach a consensus. I suspected that one of reason could be the interactivity level of visual technologies. In addition, in the first two essays, I focused on an expert group. Therefore, I did not know how effects of visual technologies differ in an expert group and a novice group. Furthermore, in essay 1, I found that visual technologies affected decision bias but not accuracy. That is, by using more visual technologies, group members were less likely to over predict the level of ozone. I suspected visual technologies can increase decision confidence, so group members did not need to over predict the level of ozone level. Therefore, the purpose of essay 3 is to answer these unknown questions.

Essay 3 focused on interactive technology, group domain knowledge, and a shift in group confidence. I answer two specific questions. First, how does the level of interactivity of a visual technology affect a shift in group confidence? Second, how does group domain knowledge affect the relationship between the level of interactivity of a visual technology and a shift in group confidence? I found that groups using a high interactive technology increased their confidence more than did groups using a low interactive technology. In addition, for novice groups, those using a high interactive technology were not different from those using a low interactive technology in terms of a shift in group confidence. However, for expert groups, those using a high interactive technology increased their confidence more than did those using a low interactive technology. Essay 3 can contribute to the studies on group decision making by considering a shift in group confidence, by demonstrating effect of technology interactivity on group confidence, and by demonstrating the importance of group domain knowledge.

These three essays open up multiple avenues for future research. First, future research can examine effects of technology characteristics on decision outcomes. The essays focused on two important characteristics: representation format and interactivity level. There are two general types of representation formats: visual-based and text-based. Researchers also considered either high interactive technology or low/non interactive technology. Prior studies considered these two characteristics separately, so little is known about how these characteristics interact in their effects on decision outcomes. For example, how text-based interactive technology and visual-based interactive technology differ in their effects on decision accuracy is needed for future discussion.

Second, future research can identify conditions under which decision making groups can use visual technologies to improve performance. Previous studies have demonstrated that visual technologies can facilitate the finding of patterns and insights. However, in the essay 1, I found that visual technologies cannot increase group accuracy in a forecasting task. Therefore, future research can examine why visual technologies cannot enhance forecasting accuracy.

Third, how effects of visual technologies differ in a face-face group and a virtual group is unknown. Virtual groups are becoming increasingly important and common in many business organizations. Previous studies demonstrated that virtual groups have difficulty in reaching a consensus. Therefore, future research can examine whether visual groups can benefit from using visual technologies more than can face-to-face groups in terms of consensus development and decision accuracy.

APPENDIX A

Table A.1: Technologies, Characteristics, and Use

Name	Description	Visual/non-visual IT	Information amount	Interactivity level	Frequency of use
NOAA model	Four contour plots from NOAA's national weather service, including a 1-hour ozone concentration plot, 8-hour ozone concentration plot, 1-hour surface smoke plot, and 1-hour vertical smoke integration plot.	VT	10.06	3	16
GT model	A contour plot based on a forecasting model developed at the Georgia Institute of Technology.	VT	13.89	3	6
UAM	A contour plot based on the Urban Airshed Model in Forecast Mode (UAM-FM).	VT	10.64	3	1
850mb	A contour plot of temperature in Celsius at the 850 mb level showing where warm air and cold air are located. The 850 mb temperature is also an indicator of type of precipitation.	VT	8.57	1	53
700mb	A contour plot at the 700 mb level showing vertical wind velocities, heights, temperature, and wind vectors.	VT	8.57	1	8
500mb	A contour plot at the 500 mb level. Referred to as the steering level as most weather systems and precipitation follow the winds at this level.	VT	8.57	1	23
300mb	A contour plot at the 300 mb. Referred to as the jet stream level.	VT	8.57	1	1
Skew-T	A plot used by meteorologists to analyze data from a balloon sounding. Temperature is plotted by height as denoted by pressure.	VT	8.75	1	36
KATL	Current surface meteogram for Atlanta, GA.	VT	8.10	1	4
Radar	Provides reflectivity, velocity, and rainfall information from meteorological radars placed at various locations across the US.	VT	17.34	4	7
Visible satellite imagery	Cloud cover images generated by geostationary satellites orbiting 22,000 miles above the equator looking at the United States.	VT	16.95	2	22

Name	Description	Visual/non-visual IT	Information amount	Interactivity level	Frequency of use
Water vapor imagery	Useful for pointing out regions of moist and dry air, which also provides information about the swirling middle troposphere wind patterns and jet streams. Darker colors indicate drier air while the brighter the shade of white, the more moisture in the air.	VT	16.95	2	11
GASP imagery	Aerosol optical depth images from geostationary operational environmental satellites.	VT	21.27	3	1
NAM	Contour plots from the North American Mesoscale model. This model gives forecast information out to 48 hours.	VT	12.01	2	99
NAM-BUFKIT	A visualization and analysis tool for the NAM forecasting model.	VT	12.01	3	11
NGM	Contour plots from the Nested Grid Model.	VT	12.01	2	7
RUC	Contour plots from the Rapid Update Cycle forecast model out to 12 hours.	VT	12.01	1	21
GFS	Contour plots from the Global Forecast System out to 120 hours.	VT	12.01	1	46
GFDL	5-day forecast of hurricanes from NOAA's Geophysical Fluid Dynamics Laboratory.	VT	13.66	2	2
Regression model	Output estimated from a set of variables, such as cloud cover, temperature, dew point, pressure, wind speed, and wind direction.	NVT	6.64	0	16
Nearest neighbor model	Ozone 8-hour maximum estimated from the latest "Nearest Neighbor" ozone forecasting model for Atlanta.	NVT	6.64	0	11
CART model	Predicts next-day's Air Quality Index 8-hour ozone maximum for Atlanta. Combines historical data with chemical and weather predictions	NVT	5.88	0	11
Chat room	A medium for forecasters to post individual comments, discuss with others, and check historical meeting information.	NVT	3.30	1	457

Note: We consider a technology as providing visual representation if it includes a graph or map. Technologies that provide solely text information were identified as non-visual. The 23 technologies available to the team vary in terms of the number of variables on which information is provided and the number of observations for each variable. For each technology, we computed the amount of information available to the decision maker (Lurie 2004) using the information theoretic measure of entropy of the product of the number of variables and the number of observations shown at a time in the default setting for a technology). For each technology, we counted the presence of eight characteristics of interactive visualizations (Thomas and Cook 2005; Yi et al. 2007b+ animation cite): (1) select, (2) explore, (3) reconfigure, (4) encode, (5) abstract/elaborate, (6) Filter, (7) connect, and (8) animate. Each technology was assigned an interactivity score ranging between 0 and 8 based on the number of these characteristics present in the technology. Frequency is the total number of times the technology was used during the data collection period (2006-2008).

APPENDIX B

Table B.1: Use of Visual Representation Technologies

	OLS		Cochrane-Orcutt Procedure		OLS (chance-corrected)	
Independent Variables	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Intercept	-14.839	-2.15*	-14.824	-2.10*	-12.587	-1.86†
Weekday	6.610	2.28*	6.479	2.21*	6.480	2.28*
June	13.464	2.96**	13.158	2.72**	13.200	2.96**
July	10.389	2.40*	10.051	2.17*	10.185	2.40*
August	4.727	1.08	4.437	0.96	4.635	1.08
September	-4.269	-1.09	-4.705	-1.13	-4.186	-1.09
Year2007	14.392	4.37**	14.396	4.11**	14.109	4.37**
Year2008	11.394	3.53**	11.363	3.30**	11.170	3.53**
Team Size	3.523	3.24**	3.663	3.32**	3.454	3.24**
Lack of Consensus	0.046	1.07	0.044	1.05	0.045	1.07
Exactingness (YO)	-3.853	-1.01	-4.363	-1.12	-3.777	-1.01
Exactingness (OR)	12.943	1.73†	12.480	1.67†	12.689	1.73†
VC_YO	0.224	3.12**	0.216	3.04**	0.220	3.12**
VC_OR	0.177	2.21*	0.186	2.44*	0.173	2.21*
Log Information Amount						
R^2	0.176		0.165		0.176	

Note 1: Dependent Variable = RATIO OF VISUAL IT USE

Note 2: ** $p < .01$, * $p < .05$, † $p < .10$. VC_YO = Lack of Consensus* Exactingness (YO); VC_OR = Lack of Consensus* Exactingness (OR)

Table B.2: Effect of Visual Representation Technology Use on Performance

	OLS		Cochrane-Orcutt Procedure		2SLS		OLS (chance-corrected)	
Independent Variables	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Intercept	4.056	1.40	4.945	1.61	4.028	1.38	4.143	1.43
Weekday	-1.546	-1.29	-1.539	-1.26	-1.524	-1.28	-1.546	-1.29
June	0.462	0.27	0.152	0.07	0.503	0.29	0.462	0.27
July	2.675	1.58	2.447	1.14	2.711	1.59	2.675	1.58
August	0.901	0.54	0.821	0.39	0.906	0.55	0.901	0.54
September	4.143	2.70**	3.830	1.94†	4.129	2.69**	4.143	2.70**
Year2007	0.237	0.16	0.029	0.02	0.253	0.17	0.237	0.16
Year2008	0.147	0.11	-0.060	-0.04	0.167	0.12	0.147	0.11
Team Size	-0.629	-1.24	-0.734	-1.49	-0.627	-1.24	-0.629	-1.24
Lack of Consensus	-0.027	-1.44	-0.021	-1.15	-0.027	-1.44	-0.027	-1.44
Exactingness (YO)	1.634	1.06	0.964	0.61	1.605	1.04	1.634	1.06
Exactingness (OR)	9.247	2.51*	9.653	2.49*	9.249	2.51*	9.247	2.51**
VC_YO	0.041	1.20	0.040	1.17	0.042	1.21	0.041	1.20
VC_OR	-0.064	-1.53	-0.055	-1.29	-0.064	-1.52	-0.064	-1.53
Effort	0.013	1.80†	0.012	1.81†	0.013	1.82†	0.013	1.80†
Ratio of Visual IT Use	-0.044	-2.08*	-0.040	-2.03*	-0.047	-1.98*	-0.044	-2.08*
R^2	0.073		0.062		0.073		0.073	

Note 1: Dependent Variable = BIAS

Note 2: ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$. VC_YO = Lack of Consensus* Exactingness (YO); VC_OR = Lack of Consensus* Exactingness (OR)

Table B.3: Effect of Visual Representation Technology Use on Performance

	OLS		Cochrane-Orcutt Procedure		2SLS		OLS (chance-corrected)	
Independent Variables	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Intercept	8.549	4.84**	8.641	4.75**	8.588	4.85**	8.559	4.85**
Weekday	0.078	0.10	0.122	0.16	0.047	0.06	0.078	0.10
June	2.368	2.21*	2.396	2.04*	2.311	2.17*	2.368	2.21*
July	3.247	3.32**	3.306	3.04**	3.196	3.27**	3.247	3.32**
August	1.560	1.47	1.634	1.40	1.553	1.47	1.560	1.47
September	1.327	1.33	1.361	1.23	1.346	1.35	1.327	1.33
Year2007	0.578	0.63	0.571	0.56	0.554	0.60	0.578	0.63
Year2008	-0.353	-0.40	-0.320	-0.33	-0.381	-0.43	-0.353	-0.40
Team Size	-0.277	-0.87	-0.324	-1.02	-0.279	-0.88	-0.277	-0.87
Lack of Consensus	-0.002	-0.13	-0.001	-0.08	-0.002	-0.13	-0.002	-0.13
Exactingness (YO)	0.720	0.70	0.769	0.73	0.763	0.75	0.720	0.70
Exactingness (OR)	4.784	2.03*	4.505	1.87†	4.781	2.04*	4.784	2.03*
VC_YO	0.009	0.30	0.005	0.17	0.008	0.28	0.009	0.30
VC_OR	-0.046	-1.28	-0.041	-1.11	-0.046	-1.32	-0.046	-1.28
Effort	0.002	0.32	0.002	0.37	0.001	0.19	0.002	0.32
Ratio of Visual IT	-0.005	-0.41	-0.005	-0.41	0.000	-0.01	-0.005	-0.41
R^2	0.047		0.041		0.047		0.047	

Note 1: Dependent Variable = INACCURACY

Note 2: ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$. VC_YO = Lack of Consensus* Exactingness (YO); VC_OR = Lack of Consensus* Exactingness (OR)

APPENDIX C

Table C.1: Sample Coding of Forecasting Discussion

Categories	Sia et al.'s (2002) Coding Scheme	Examples
Novel Argument (*Informational Influence*)	A novel argument was one that contained facts in support of the collective position and yielded fresh insights (i.e., it was not related to arguments presented earlier).	Forecaster A: With skies clearing again, lighter winds and restricted boundary layer depth, I saw us climbing again for O3. Note: "climbing" was a new insight.
Valid Argument (*Informational Influence*)	A valid argument was one that contained facts in support of the collective position and reinforced other arguments (i.e., it was related to arguments presented earlier).	Forecaster B: Agree with light downslope (NW flow) Note: One forecaster had mentioned NW flow before Forecaster B.
Pluralistic Balance Statement (*Normative Influence*)	A person was considered to have engaged in pluralistic balance behavior if he or she moved in the direction of the collective position provided no facts in support of the collective position (e.g., simply stated personal preference).	Forecaster C: I'll go with 68/19 then and update with yellow for both. Note: Forecaster C moved his/her forecast to 68 from 70.
One-upmanship Statement (*Normative Influence*)	A person was considered to have engaged in one-upmanship behavior if he or she moved in the direction of the collective position beyond the average collective position in the previous round, regardless of the arguments given.	Forecaster D: OK then 85/42 ok with me. Note: Forecaster D moved his/her forecast from 81 to 85. The collective consensus was 84.
Other	Otherwise	Forecaster E: Need to vote2-my numbers went away again.

APPENDIX D

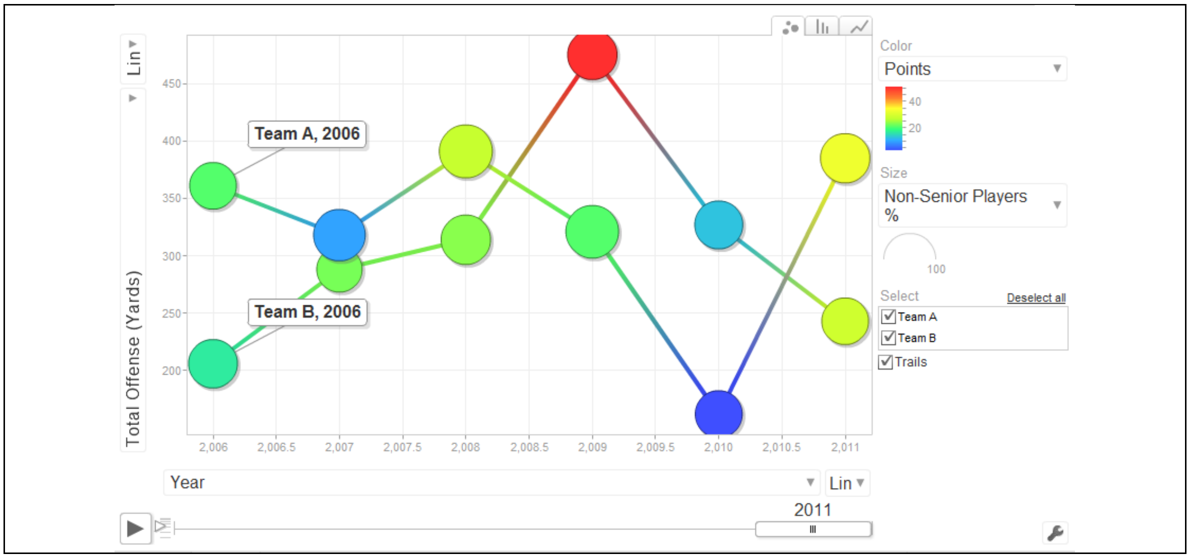

Figure D.1: High Interactive Technology

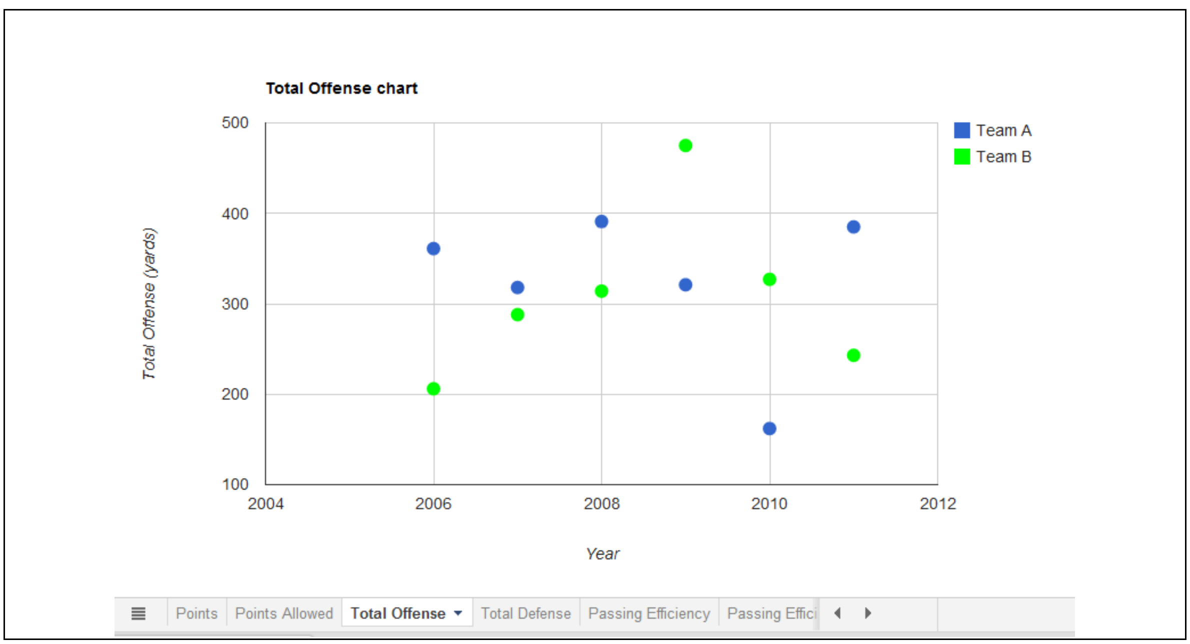

Figure D.2: Low Interactive Technology

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