Using Technology to Persuade:

Visual Representation Technologies and Consensus Seeking in Virtual Teams

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Although Fogg's (1999, 2003) ideas of persuasive technologies are widely accepted, few attempts have been made to test his ideas, particularly in a team context. In this article, we 1) theoretically extend Fogg's ideas by identifying contexts in which virtual teams are more likely to use persuasive technologies; 2) empirically measure technology visualness, a factor that likely makes technologies more or less persuasive; and 3) assess the association between the use of persuasive technologies, judgment shifts, and forecast performance in a real-world virtual team context. We identify visual representation technologies (VRTs) as a class of technologies used by virtual teams to select, transform, and present data in a rich visual format. We propose that such technologies play a persuasive, as well as diagnostic, role in virtual team decisions. Over a three-year period, we examine the daily chat room discussions and decisions of a virtual team that makes smog forecasts with large economic and health consequences. We supplement regression models of field data with an experiment, interviews with team members, and analyses of imagery processing and group cohesion in team language use. Experiment results show that, relative to non-VRTs, the use of a VRT in a forecasting task increases imagery processing. Field data results show that team members increase their use of VRTs during chat room discussions when initial team consensus is low and the environment is more exacting. Greater use of VRTs in team discussions relates to greater shifts in the initial to final consensus forecasts of the team and greater odds of the team shifting its forecast policy to issue a smog alert. Increased use of VRTs is associated with lower forecast bias but is not significantly associated with forecast accuracy. VRT use is also associated with greater imagery processing and increased group cohesion, as shown through language use.

Keywords: Virtual Teams, Consensus, Persuasion, Exactingness, Information Visualization, Decision Making, Visual Representation Technologies, Forecasting

INTRODUCTION

Organizations use teams, rather than individuals, to offer multiple perspectives on important decisions (Hackman and Morris 1975). Virtual teams enhance the range of perspectives by bringing together individuals from different organizations and locations (Martins et al. 2004). However, reaching consensus can be difficult as team members cannot leverage the richness of face-to-face interactions to overcome differences in opinions (Majchrzak et al. 2005, Sproull and Kiesler 1986, Tan et al. 1998). Although there is substantial research on how virtual teams use technology to exchange information (Powell et al. 2004), and an interest in how technologies persuade individuals (Fogg 1999, 2003), little is known about the persuasive role of technology in changing team member attitudes and seeking consensus in virtual team settings. Instead, research on virtual teams has tended to focus on team communication and information processing, i.e., computer-mediated communication (Kock 2004) and group support systems (Dennis et al. 2001).

Beyond their diagnostic role, we propose that certain types of information technologies play a persuasive role in virtual team settings. We identify a class of technologies called *visual representation technologies (VRTs)*, which select, transform, and present data in a rich visual format (Card et al. 1999, Thomas and Cook 2005), and suggest they are associated with greater informational influence in virtual team settings, perhaps by enhancing imagery processing (MacInnis and Price 1987, Petrova and Cialdini 2008). We examine the conditions in which the use of persuasive technologies, such as VRTs, is likely to increase; how team use of persuasive technologies affects shifts in judgments and changes in policy; and how persuasive technology use affects bias and accuracy in team judgments.

We identify lack of initial team consensus and environmental exactingness as important contextual factors affecting the relative need of virtual team members to use persuasive technologies when making decisions. By "use," we mean using a particular information technology, or type of technology, to gather information and referring to this technology in team discussions. Lack of consensus is a critical challenge in teams of diverse individuals (Alavi and Tiwana 2002, Zhang et al. 2007). Exactingness (defined as greater consequences of small errors of judgment; Hogarth et al. 1991) is also important, as team members need to be convinced that they are making the right decision (Eisenhardt 1989, Knight et al. 1999). The combination of low consensus and high exactingness is particularly challenging because team members must persuade others to change their minds in environments where the consequences of errors are high.

We hypothesize that virtual team members will increase their use of VRTs when initial team consensus is low and consequences of making small errors of judgment are high, that greater use of VRTs will be associated with larger shifts in the initial to final consensus judgments of the team, and that the use of VRTs will be associated with less biased and more accurate decisions. We test our hypotheses in a novel real-world setting: air quality forecasting performed by a virtual team responsible for the 5-million-person Atlanta region in the United States. The result provides a rich context for examining the persuasive role of technology in which team membership and task are relatively constant, but the decision context varies. We supplement regression models of field data with an experiment, interviews with team members, and analyses of imagery processing and group cohesion in team discussions.

Experiment results show that, relative to non-VRTs, the use of a VRT in a forecasting task increases imagery processing. Field data results show that team members increase VRT use when initial team consensus is low and the environment is more exacting. Providing evidence for VRTs as persuasive technologies, greater use of VRTs in team discussions relates to greater shifts in the initial to final consensus forecasts of the team and greater odds of the team shifting its forecast to issue a smog alert. Increased use of VRTs is associated with lower forecast bias but not forecast accuracy. Language analysis of team discussions shows that VRT use is associated with greater imagery processing and increased group cohesion.

RELEVANT LITERATURE AND HYPOTHESIS DEVELOPMENT

VRTs as Diagnostic and Persuasive Technologies

Technologies play diagnostic and persuasive roles in team settings (see Online Appendix A for a summary of information technology roles in team settings). For example, information technologies help team members exchange and diagnose information that can reduce uncertainty and minimize ambiguity in decision making (Dennis et al. 2001). VRTs have several aspects that make them useful for diagnosis such as enhancing users' ability to detect patterns in data because they engage the more efficient visual system (Lurie and Mason 2007). In forecasting contexts, VRTs can help detect extreme and consequential environmental events, such as forest fires, better than traditional tools (Al-Saadi et al. 2005).

Information technologies, in addition to their diagnostic role, can play a persuasive role in changing team member attitudes and reaching consensus (Sia et al. 2002). Fogg (1998, 1999, 2003) identifies aspects of persuasive technologies, which help them change user opinions or attitudes. Consistent with Fogg's framework, and in contrast to non-visual technologies and simple graphics examined in previous studies (Benbasat and Dexter 1985, Benbasat and Dexter 1986, Jarvenpaa 1989), VRTs have a number of persuasive aspects. For example, VRTs use multiple modalities to display information, an aspect of persuasive technologies (Fogg 2003). This includes the use of visualization, which is important to persuasion (Fogg 1998), and involves encoding data or information as visual objects. For example, in the contour weather map shown in Figure 1, wind speed is presented by wind barbs. Supporting Fogg's (1998) conjectures, prior research shows that visualization can enhance attitude change (Pandey et al. 2014). Furthermore, many VRTs use simulations--an additional affordance of persuasive technologies (Fogg 2003). Simulations allow users to see movement and change over time, leading to cause–effect attributions (Fogg 1998, Oinas-Kukkonen and Harjumaa 2009). Simulations allow users to answer "what if" questions by changing simulation options (Fogg 1999). In our context, VRTs can simulate ozone formation using meteorological and emission data.

- - - insert Figure 1 here - - -

Fogg (1998, 2003) posits that technologies that are visually attractive, and include images, are more persuasive. Visual information is more accessible, 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). Moreover, visual information is more vivid and requires fewer cognitive resources to process than non-vivid information (Keller and Block 1997). Thus, VRTs may engage gestalt and automatic processes that are simple for human decision makers, such as the ability to recognize patterns (Kosslyn

1994, Larkin and Simon 1987, Sloman 1996), enhancing their persuasiveness. VRTs may further enhance persuasion by engaging imagery processing (MacInnis and Price 1987, Petrova and Cialdini 2008). Imagery processing, as compared to discursive processing, is shown by greater ease of imagination, perceived vividness, emotional response, and use of sensory-arousing words in communication (Bone and Ellen 1992, Emrich et al. 2001, Friendly et al. 1982, Holmes et al. 2008).

Research suggests that differences in information processing also occur when one is talking about (but not actually viewing) a physical image. Substantial research shows a strong link between the cognitive and neurological processes involved in talking about and actually seeing physical images (Kosslyn et al. 1999, O'Craven and Kanwisher 2000). References to images activate brain regions that overlap with those active when the object is actually viewed (Chao et al. 1999, Chao and Martin 2000, Grèzes and Decety 2002, Just et al. 2004, Magnussen and Helstrup 2007, Mellet et al. 2002). In addition, brain regions involved in the processing of images are activated when people read high-imagery sentences (Just et al. 2004). The cognitive processes associated with seeing, imagining, and referencing images, and seeing and using imagery words, are the same. In the context of our study, this suggests that using a (visual) map of a storm in team discussions should make visualizations of the storm easier for team members and could increase team estimates of an incoming storm.

References to images can be particularly important in team contexts. For example, references to mental images can help resolve conflict in organizational settings (Von Glinow et al. 2004). Other studies show that the picture-superiority effect, in which recall is higher for pictures than words (Paivio and Csapo 1973), is stronger for teams than individuals, even for private information known only by one person (Weldon and Bellinger 1997), and that using images to illustrate ideas helps persuade other group members (Stigliani and Ravasi 2012). In sum, multiple modalities of VRTs, including the use of visualization, simulation, and visual imagery, as well as greater visual attractiveness, should make VRTs more persuasive (Fogg 2003, Oinas-Kukkonen and Harjumaa 2009). These characteristics should enhance the use of VRTs in team settings when the need to persuade is higher.

To explore the idea that the use of VRTs enhances imagery processing, we conducted a preliminary experiment in which undergraduate participants who had taken a meteorology course were randomly assigned to use either a VRT or non-VRT forecasting technology, which had identical weather information, to predict air quality for the next day. The VRT was a Google Motion Chart and the non-VRT was a Microsoft Excel sheet (see Online Appendix B). Participants forecast the air quality for the following day and then read the following statement: "The weather technology forecasts a decrease in moisture and instability recently. The weather technology suggests that the chance of precipitation is reducing significantly. Low chances of rainfall and low moisture. Therefore, the air quality should be good tomorrow." Imagery processing was measured using the mean of two items (Bone and Ellen 1992, $r = .74$): "As you read this statement, to what extent did any images come to mind" (1 = to a very small extent; 7 = to a very large extent). "While reading this statement, I experienced" (1 = few or no images; 7 lots of images). ANOVA results showed that imagery processing was greater among participants in the VRT versus non-VRT condition ($M_{VRT} = 3.92$ vs. $M_{NON\text{-}VRT} = 3.08$; $F(1, 23) = 4.86$, $p < .05$), supporting the idea that VRT use may be associated with greater imagery processing.

Lack of Consensus, Exactingness, and VRT Use

Reaching consensus is often challenging for team members, given the diversity of and geographic distance between virtual team members, time pressure, and difficulty in communicating ideas in online settings. Difficulties in reaching consensus may not be overcome even through technologies with greater social presence and media richness (Dennis et al. 2008, Dennis et al. 2001, George et al. 1990, Kock 2004, Miranda and Saunders 2003, Montoya-Weiss et al. 2001, Straub and Karahanna 1998), suggesting that virtual teams will seek other ways to overcome differences. One way to reach consensus may be by using technologies with greater persuasive power.

Another important variable affecting virtual team decisions is the exactingness or the *consequences of making small errors of judgment* (Hogarth et al. 1991). When exactingness is high, the consequences of making an error are large. In these conditions, the need to resolve differences in team member opinions increases because team members share the cost of making a wrong decision. More exacting situations also increase the need for decision makers to believe that they have reached a correct decision. Therefore, the use of persuasive technologies should be even more beneficial.

We predict that lack of consensus interacts with environmental exactingness to affect VRT use. That is, the extent to which team members need to influence other members depends on the interaction of team consensus and environmental exactingness. When consensus is high, there is little need for team members to use VRTs regardless of the level of environmental exactingness. Similarly, under low consensus and low exactingness, where making the right decision is less critical and small changes in the team consensus recommendation have a limited impact on outcomes, persuading others should be less necessary. However, when consensus is low and exactingness is high, team members will need to be persuaded to alter their decisions, which should increase the use of persuasive technologies. In other words, exactingness should moderate the effects of low consensus on the use of persuasive technologies.

HYPOTHESIS 1 (H1): *The association between lower initial consensus and increased use of VRTs in team discussions increases with environmental exactingness.*

VRTs and Persuasion

In addition to hypothesizing an interaction between initial team consensus and environmental exactingness on the use of VRTs, we posit that the use of VRTs will be associated with enhanced team persuasion. Following prior research (O'Keefe 1990, Simons 1976), we define persuasion as a communication process in which people affect opinions or attitudes of others (Cialdini 2009). Successful persuasion is evidenced by shifts in beliefs, opinions, attitudes, or choices (El-Shinnawy and Vinze 1998, Sia et al. 2002) and can be measured through the magnitude and likelihood of judgment and policy shifts (El-Shinnawy and Vinze 1998, Sia et al. 2002). If greater VRT use enhances team persuasion, it should lead to greater differences between the initial and final consensus judgments of the team.

HYPOTHESIS 2 (H2): *Greater use of VRTs is associated with (a) greater shifts in a team's initial to final consensus judgments and (b) greater likelihood of a shift in recommended policies.*

VRTs and Team Performance

We have argued that the use of VRTs is positively related to persuasion, as indicated by shifts in team judgments and policies. However, whether the use of VRTs is associated with higher team performance is not clear. Indeed, prior research has found mixed effects of information technology use on team performance (Driskell et al. 2003, Martins et al. 2004). For example, some studies have found no difference (Cappel and Windsor 2000), whereas others have found that computer-mediated teams sometimes perform worse (Andres 2002), or better (Schmidt et al. 2001), than face-to-face teams.

In forecasting tasks, bias and accuracy are the primary measures of performance (Durand 2003). Bias is the difference between predicted and observed forecast levels. Negative values for bias reflect a tendency to underpredict, whereas positive values suggest a tendency to overpredict. By contrast, accuracy is the absolute value of the difference between predicted and observed values. More accurate predictions are shown by values closer to zero. Conversely, higher values reflect greater inaccuracy.

Although most teams seek to minimize bias, some teams tend to bias their decisions. The tendency to be positively or negatively biased depends on the consequences of underprediction or overprediction. For example, weather forecasting teams are more likely to overpredict than underpredict severe weather events because their primary responsibility is public safety. Given this, we propose that greater use of VRTs will reduce decision bias. In particular, to the extent that VRTs are more persuasive, their use should increase decision confidence (Fogg 2003, Oinas-Kukkonen and Harjumaa 2009). If teams are more confident in their forecasts, then they should be less likely to bias their forecasts to mitigate the consequences of being wrong. Since accuracy is the absolute value of bias, greater use of VRTs should also be associated with greater accuracy.

HYPOTHESIS 3 (H3): *Greater use of VRTs is associated with a) decreased forecasting bias and b) increased forecasting accuracy.*

METHOD

Research Setting

To evaluate our hypotheses, we conducted a field study using daily chat room discussion data as well as predicted and actual air quality levels from a virtual smog forecasting team in Atlanta, Georgia, from 2006 to 2008. The team in our study is composed of 10 research scientists from a major research university in Georgia and the state's Environmental Protection Division (EPD). Their primary task is to forecast air quality (i.e., the level of ozone pollutant concentration in parts per billion [PPB]) and make a forecast recommendation (whether to call a smog alert) for the subsequent day in the Atlanta metropolitan area and surrounding cities during the ground-level ozone season (from May 1 to September 30). During the time of our study, Environmental Protection Agency (EPA) standards specified that PPB values of 0-59 (green) were considered "good," 60-75 (yellow) "moderate," 76-95 (orange) "unhealthy for sensitive groups," 96-115 (red) "unhealthy," 116-374 (purple) "very unhealthy," and over 374 (brown) "dangerous," but conditions in this range have never occurred in Georgia. In Atlanta, smog alerts are issued in the orange, red, and purple zones.

Air quality forecasting is difficult given the unpredictability of weather and the health and economic costs of making an incorrect forecast. Excessive ozone exposure has significant health consequences, particularly for individuals with respiratory problems who should stay indoors when ozone levels are high. Air pollution accounts for 10,000 premature deaths per year in the United States (Caiazzo et al. 2013). However, declaring a smog alert is costly with an economic loss of $58.63 million annually due to school absences alone on smog alert days in Los Angeles (Hall et al. 2008). As smog alert frequency increases, individuals reduce ozone avoidance behavior putting themselves at greater risk (Neidell 2006).

The team uses a custom website to access forecasting technologies. 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. Non-visual technologies, such as the weather diagnostics tool in Figure 2, provide textual and numeric information including temperature readings, air speed, and dew point and contain few visual images. VRT technologies are found at the other end of the spectrum, such as the 850 mb contour satellite weather map in Figure 1, which presents visual images and uses color to convey differences in information but also shows numeric information such as air pressure, wind speed, and temperature. Online Appendix C provides details on the portfolio of information technologies available to the team.

Every day at 1:30 p.m., during the ground-level ozone season, the smog forecasting team meets in an Internet chat room to discuss and reach consensus on the team's ozone forecast for the following day. Before joining the chat room, each team member inputs his or her initial forecast. Individuals are not allowed to view other forecasts, prior to submitting their own forecasts. Before the discussion, the website computes the average of individual forecasts which serves as the team's initial forecast of the ozone concentration for the next day. During the discussion, individual team members often defend or clarify their predictions using particular information technologies. The team must reach a consensus forecast. The forecast includes the predicted ozone concentration level for the next day and the recommendation of whether to call a smog alert. Team forecasts are posted on the State of Georgia's EPD website by 2 p.m. and sent to the news media by e-mail.

Figure 3 shows an online chat on the day the team issued a smog alert. The team's initial forecast is 93 PPB—equivalent to an orange level smog alert in which conditions are considered unhealthy for sensitive groups. During the discussion, proponents of a higher forecast level use VRTs to convince the team to raise the forecast to 96 PPB—equivalent to a red level alert in which ozone levels are considered unhealthy for all. For instance, Forecaster A uses wind information from the NAM model to support the argument that the forecast ozone level should be higher. This leads others (e.g., Forecaster C) to agree to a higher-level alert. The actual ozone reading for the next day is captured by sensors in the field.

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Data Collection

We obtained observed ozone values for each day during the ground-level ozone season in 2006, 2007, and 2008 from the Ambient Monitoring Program database of the Georgia EPD. The team makes ozone forecasts for May, June, July, August, and September each year. From the smog forecasting website, we extracted (1) initial individual forecasts of the ozone concentration for the next day, (2) the team's final consensus forecast, and (3) the text of the team's online chat. We also interviewed key informants from the virtual team—one research scientist from a major university and two scientists from the EPA in Atlanta—and observed a meeting in which the team made a smog prediction, after which we asked team members questions about the forecast process.

Dependent Variables

Technology Visualness Corrected for Chance. To assess the extent of VRT use, we first examined the full range of the 22 technologies available to the team. We compute a technology's *visualness* by dividing the number of information attributes presented in a visual format (e.g., graphic images rather than numbers) by the total number of different attributes. For instance, the 850 mb plot shown in Figure 1 includes seven information attributes: Four are presented in a visual format (contour height, contour temperature, wind speed, and wind direction), and three are presented in a non-visual format (temperature, dew point, and pressure). Thus, the visualness of the 850 mb plot technology is 4/7 = 57%.

We calculate VRT use as the average visualness of technologies used by the team on a particular day *Technology Visualness* (*TV*). *TV* controls for potential difference in the number of technologies used. For example, in the chat room discussion shown in Figure 3, the team used three technologies (NGM, NAM, and Bufkit), whose visualness measures are all 100%, so *TV* on that day is equal to 100%. To correct the percentage of information (76%) that is visual across all available technologies, following Lurie (2004), we compute *Corrected Visualness* (*CV*) on day *i* as $\overline{CV_i} = \frac{TV_i - P_i}{1 - P_i}$, where $\overline{CV_i}$= corrected technology visualness, TV_i= unadjusted technology visualness, and P_i= the percentage of information that is visual across all available technologies. For example, in the chat room discussion shown in Figure 3, *Corrected Visualness* is (100% - 76%)/(1 – 76%) = 1. We use the corrected measure of technology visualness (*CV*) in our analysis.[1]

[1] Online Appendix C shows the technology visualness, corrected visualness, information amount, and reference frequency of each technology available to the team.

Persuasion. Persuasion in team settings can be measured as change from the average judgments—or choices of individual team members prior to discussion, to the group's consensus judgment—or choice after discussion as well as categorical shifts in policy (El-Shinnawy and Vinze 1998, Sia et al. 2002). Following prior research (e.g., Crott et al. 1991, El-Shinnawy and Vinze 1998), *Forecast Shift* is the difference between the final and the initial team forecasts in PPB for each day. We measure policy shifts in ozone severity levels using a categorical variable, *Up-Down Shift*, coded as "0" if the team's initial and final ozone severity level decisions are the same, "-1" if the team shifts to a lower (less serious) ozone severity level (e.g., from yellow to green), and "+1" if the team shifts from an initial severity level to a higher (more serious) severity level (e.g., from yellow to orange).

Team Performance. We compute forecast *Bias* as the difference between predicted and observed ozone concentration, divided by the observed ozone concentration level. Negative values indicate underprediction, whereas positive values indicate overprediction. To ease interpretation, we compute the *Inaccuracy* of the forecast as the absolute value of forecast bias. Larger numbers indicate greater inaccuracy. To facilitate interpretation, bias and inaccuracy are multiplied by 100.

Independent Variables

Following prior research (Lahiri and Teigland 1987), initial team consensus (*Lack of Consensus*) is measured as the variance in initial individual forecasts on a given day. We use two binary variables to represent exactingness and code *YO* as "1" if the initial team perception is within 5 PPB of the yellow-orange border and *OR* as "1" if the initial team perception is within 5 PPB of the orange-red border and "0" otherwise.[2]

[2] Interviews and discussion after observing the team forecasting process revealed that team members perceive forecasts near the yellow-orange and orange-red smog alert borders as the most exacting. The yellow-orange border potentially involves issuing a smog alert for sensitive individuals, and the consequences of making an error in issuing or failing to issue a smog alert are even larger for the orange-red border. The team did not express similar concerns about the green-yellow border as it does not involve a smog alert. Team members indicated that initial forecasts within 5 PPB of a color category border require further consideration. Using 4 PPB and 6 PPB shows consistent results. Using continuous rather than binary measures of exactingness, coding *YO* as "5" if the initial team perception was within 1 ppb of the yellow-orange border, "4" if the initial team perception was within 2 ppb, "3" if the initial team perception was within 3 ppb, "2" if the initial team perception was within 4 ppb, "1" if the initial team perception was within 5 ppb, "0" otherwise, and likewise for *OR*, leads to similar results.

Control Variables

To control differences in ground-level ozone concentrations on weekdays versus weekends, as well as holiday, month, and year effects (US Environmental Protection Agency 2003), we code *Weekday* as "1" for Monday to Friday and "0" otherwise. We code *Holiday* as "1" for holiday and "0" otherwise. We also use 14 binary variables, *Jun06* through *Sep08* to distinguish month–year pairs from the base month of May in 2006 (i.e., *May06*).

For each day, we include *Team Size* as the number of forecasters who posted an initial forecast. Based on academic training, we classify each team member as "meteorologist," "environmental geochemist," "statistician," or "other." We also identify whether the team member is located at a major research university in Georgia or at the state's EPD as well as their gender. Following past research (Knight et al. 1999), the daily expertise diversity, location diversity, and gender diversity of the team are computed using Blau's heterogeneity index, $(1-\sum p_i^2)$, where p_i is the proportion of the team in the *i*th category participating in the team discussion for that day. We control for team participation by dividing the number of forecasters who participate in a team discussion by the number of forecasters who post their initial forecast on a particular day. We include forecaster dummies to account for individual differences in forecasting behavior and team influence. To control for the amount of information available to the team, we compute the product of the number of information attributes and the number of observations shown at a time in the default setting for a technology and calculate the average amount of information for technologies used on a particular day (*Information Amount*).

ANALYSIS AND RESULTS

The data on technology use, environmental exactingness, and initial team consensus for each day in the ozone season in each year yielded 457 daily observations from 2006-2008. Table 1 reports the means, standard deviations, and correlations of the variables in the analysis. Pairwise correlations between the independent and control variables in our analysis are modest with values below .40.

Use of VRTs

Hypothesis 1 posits a moderating relationship between lack of consensus and environmental exactingness on the use of VRTs, such that at lower levels of consensus, exacting environments will be associated with greater use of such technologies. OLS results, shown in Model 2 of Table 2, *Lack of Consensus* × *YO* ($\beta = .012$, $p < .01$) and *Lack of Consensus* × *OR* ($\beta = .007$, $p < .10$), are positively associated with *Corrected Visualness*. A joint test of these two interactions yields an F value of 4.63, $p = .01$, showing that overall, exactingness moderates the relationship between the lack of consensus and the use of VRTs. For robustness, given the time-series nature of the data, we re-estimated the technology visualness model using the Cochrane-Orcutt procedure and found consistent results, leading us to conclude that serial correlation is not an issue in our data (see Online Appendix D). As an additional robustness check, we coded each statement in each team chat as either 1) initial average, 2) agreement statement, 3) persuasion attempt using VRTs, 4) persuasion attempt not using VRTs, or 5) other statement. Re-estimated the model, substituting the proportion of VRT persuasion attempts for the dependent variable led to similar results (see Online Appendix E). Therefore, Hypothesis 1 is supported.

Impact of VRTs on Persuasion

Tobit model results in Table 3 show that VRT use is positively related to shifts in initial to final forecasts ($\beta = .026$, $p < .05$).[3] A multinomial logistic model for *Up-Down Shift*, testing whether the use of VRTs relates to upward or downward shifts in the initial to final team forecast policy, indicates that, while an increase in the use of VRTs increases the relative log odds of shifting to a more serious ozone level ($\beta = .359$, $p < .01$), an increase in the use of VRTs does not affect the relative log odds of shifting to a less serious level ($\beta = -.056$, $p > .10$). That is, the team is more likely to shift to a more serious ozone level as VRT use increases. In summary, these results provide support for Hypotheses 2a and 2b.

[3] Because the team did not shift forecasts every day, there are days for which *Forecast Shift* equals 0 and OLS estimates may be biased and inconsistent (Greene 2003). Since we are interested in the relationship between VRT use and policy change (i.e., *Forecast Shift* > 0 or *Forecast Shift* < 0). Thus, a two-limit Tobit regression is appropriate. The lower limit is -1 (a shift to a lower ozone level) and the upper limit is 1 (a shift to a higher level).

VRT Use and Performance

Table 4 displays the results of regression analyses for *Bias* and *Inaccuracy*. Supporting Hypothesis 3a, but not 3b, we find a significant effect of *Corrected Visualness* on *Bias* (β = -1.400, p < .05) but, while the coefficient is in the expected direction, the results for *Inaccuracy* are not significant (β = -.567, p > .10). Thus an increase in VRT use is associated with a reduction in team forecast bias but not significantly improved forecast accuracy.

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Use of VRTs and Imagery Processing

To gain further insight into why VRT use may enhance persuasion in virtual teams, following Just et al. (2004), we explore whether mentions of VRTs in group discussions are associated with language reflecting imagery processing (Emrich et al. 2001, Friendly et al. 1982, Martindale 1975, Seyranian and Bligh 2008). For each daily team discussion, we count the number of image- and concept-based words in the chat using Martindale's (1975) regressive imagery dictionary of 2,900 image words (e.g., imagine, see, rock, journey).[4] We regress the number of image-based words on VRT use, controlling the total number of words. We find a significant effect of *Corrected Visualness* on the use of image-based words (β = .68, p < .00). By contrast, regressing the number of concept-based words on VRT use does not show a significant effect of *Corrected Visualness* (β = .28, p > .10). Consistent with the experiment, these findings show that the use of VRTs is associated with image (but not concept) words and imagery language and offer a possible mechanism for the observed results. In addition, forecaster interviews indicate that team chats convey images of forecasting technology outputs. For example, one said "we can imagine what the forecaster is saying without looking at the model." As with the preliminary experiment, language analysis and interviews support the proposal that VRT mentions in team chats may invoke imagery processing by team members.

[4] For example, in Figure 3, "deeper," "lower," and "cloud" are image words, whereas "reason," "why," and "agree" are concept words. Image-based words evoke mental images of things or events, whereas concept-based words evoke logical interpretations in the minds of readers/listeners (Emrich et al. 2001, Friendly et al. 1982). Word classification was performed using Yoshikoder (www.yoshikoder.org).

Use of VRTs and Group Cohesion

We have argued that VRTs help teams reach consensus and enhance team persuasion. That is, such technologies lead to shifts in team decisions and help teams coalesce around these decisions. Previous studies (e.g., Dennis et al. 2008, Sarker et al. 2010, Zhang et al. 2011) investigate the relationship between technology usage and team interaction, using communication content to measure group social dynamics (Chung and Pennebaker 2014, Gonzales et al. 2010). Building on this work, we examine how VRT use is associated with group cohesion, as measured through language use. We focus on group cohesion because it is related to team consensus and persuasion (Yoo and Alavi 2001). Following Gonzales et al. (2010), we take two approaches to examine group cohesion: (1) the use of first-person plural pronouns and (2) linguistic style matching (LSM) in daily team chats. We employ the Linguistic Inquiry and Word Count program (Pennebaker et al. 2007) to assess the use of first-person plural pronouns (e.g., "we," "us") and nine function words (auxiliary verbs, common adverbs, personal pronouns, impersonal pronouns, articles, prepositions, conjunctions, negations, and quantifiers). Following previous studies (Ireland and Pennebaker 2010, Ludwig et al. 2014), we measure LSM as the extent to which the intensity of function words in a given team chat is similar to the average intensity in all team chats. We average the nine LSM scores to generate a composite LSM score. A greater composite LSM score indicates greater linguistic style matching. A regression showed a significant effect of *Corrected Visualness* on the use of first-person plural words ($\beta = .038$, $p < .05$) as well as composite LSM ($\beta = .026$, $p < .01$). These results support the idea that greater VRT use is associated with greater group cohesion.

DISCUSSION AND CONCLUSIONS

Drawing on the pioneering work by Fogg (1998, 1999, 2003), we propose that VRTs play important persuasive and diagnostic roles in virtual teams. We identify low-consensus and high exacting contexts as those in which the use of persuasive technologies should increase. We posit that increased use of these technologies in team discussions is associated with enhanced persuasion, as shown through greater shifts in team policies, and that VRT use is associated with improved decision performance by virtual teams. We test our ideas using an experiment, archival data, team observation, and interviews.

Discussion of Findings

Results from our study of the virtual team responsible for forecasting ozone levels and issuing smog alerts for the 5-million person Atlanta region confirm many of our hypotheses. In particular, the team increases its use of more visual technologies when initial team consensus is low and the consequences of small errors of judgment are large. These findings add to prior research showing how task characteristics determine technology choice (Dennis et al. 1988, George et al. 1990, Straub and Karahanna 1998).

Our prediction of a relationship between the use of VRTs and persuasion is supported. Greater use of VRTs in team discussions is associated with a larger shift between initial and final consensus forecasts and greater likelihood that the team shifts its forecasts to a more serious ozone severity level in which smog alerts are issued. These results are materially significant, given the economic and health consequences of issuing smog alerts. These findings add to research showing that technology choice can affect persuasion (El-Shinnawy and Vinze 1998, Sia et al. 2002). Importantly, the use of VRTs is associated with greater persuasion even in the absence of increased communication channels or social presence.

Our analyses provide partial support for a positive relationship between VRT use and decision quality, showing that the use of VRTs in team discussions reduces decision bias; in the context we study, a tendency to over-predict smog levels in the interest of public safety is found. The use of VRTs may help to 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). However, VRT use is not significantly associated with decision accuracy. One possible explanation may be that, while VRTs facilitate the detection of patterns in data, the activation of intuitive decision processes may also lead virtual teams to draw false inferences from the data (Kahneman 2011).

The results of the preliminary experiment in which exposure to VRTs was manipulated and imagery processing measured through scales show that, relative to using non-VRTs, the use of VRTs increases imagery processing. Analysis of team language use provides additional supportive evidence as shown by a significant association between the use of VRTs and use of image-based, but not concept-based, words in team discussions. To the extent imagery processing is associated with persuasion (Green and Brock 2000, Green and Brock 2002, Keller and Block 1997, Keller and McGill 1994, Lee 2004, Lee and Labroo 2004, Petrova and Cialdini 2008, Sherman et al. 1985, Tormala et al. 2002), this may explain why visualization and imagery are important elements of persuasive technologies (Fogg 1999, 2003). Additional analyses show that the use of VRTs is associated with greater group cohesion, indicated by the use of first-person plural pronouns and LSM (Gonzales et al. 2010). These results provide insights into how VRTs affect team interactions and support the idea that VRTs can help virtual teams reach consensus.

Theoretical Implications

Although the ideas presented by Fogg (1999, 2003) on persuasive technologies are widely accepted, few attempts have been made to test them. This article tests some of these ideas in a real-world virtual team setting. Our findings are important because they identify an overlooked role for technologies that are traditionally thought of as diagnostic tools and highlight the "persuasive" role of these technologies. Beyond the capacity to draw on and display different types of information and aid diagnosis, information technologies vary in the extent to which they are persuasive (Fogg 1999, 2003). By focusing on the persuasive role of technologies in virtual team settings, we contribute to research focused on IT as a tool for communication (e.g., Daft et al. 1987) and decision support (e.g., Todd and Benbasat 1999, Zigurs et al. 1988).

Our research provides an approach to empirically examine persuasive technologies in team settings. Future researchers can build on our research by 1) accounting for virtual teams' use of persuasive information technologies beyond those designed specifically to support communication and decision making; 2) measuring or manipulating technology visualness and other factors likely to affect persuasion and consensus building in team settings; and 3) assessing the impact of persuasive technologies on virtual team dynamics, persuasion, consensus, and performance.

Furthermore, we contribute to research on information visualization and its impact on virtual team decision making. Although prior research has argued that visualization has beneficial effects on human cognition (Card et al. 1999, Thomas and Cook 2005), and some conceptual work has focused on the impact of visualization on decisions by individuals (Lurie and Mason 2007), few attempts have been made to identify when visualization technologies are likely to be used and few attempts to measure the relationships among visualization technology use, dynamics, and/or performance, particularly in virtual team settings.

Finally, our use of longitudinal data from the historical record of a virtual team's chatroom discussions contributes to prior literature based on survey or experimental data (e.g., El-Shinnawy and Vinze 1998, Majchrzak et al. 2005, Sia et al. 2002). Our longitudinal field study design complements experimental studies on virtual teams and enables us to examine the decision making of an expert team over time with large health and economic consequences and for which the consequences of making small errors are significant. Such a setting would be difficult to mimic in a laboratory.

Managerial Implications

As virtual teams continue to play an important role in many organizations, this study has the potential to offer important managerial implications. When deploying IT for use in virtual team settings, managers should consider their effects on individual decision makers and on team processes. That is, even technologies not explicitly designed for team communication or information processing (Daft et al. 1987, Zigurs et al. 1988) may help teams reach decisions in exacting conditions. Our research also points to the need to consider the persuasive characteristics of technologies (Fogg 1999, 2003) in virtual team settings, in addition to functionality and usability. The idea that team members can influence one another by using technologies, and that some technologies are associated with more persuasion than others, is powerful and problematic. VRT use is associated with imagery processing, and imagery processing is associated with heuristic (i.e., "fast") decisions (Kahneman 2011). Therefore, overuse of persuasive technologies may have negative consequences on the quality of team decisions (although our results suggest that, in some cases, increased use of VRTs can reduce decision biases). Training teams on the advantages and disadvantages of persuasive technologies is important.

Limitations and Directions for Future Research

Like all types of research, our study has limitations and presents opportunities for future research. Our examination of a single-expert virtual team highly versed in the available technologies controls for differences across teams and technology familiarity. That said, verifying whether VRT use shows similar relationships for novice teams, for teams less familiar with technologies, or for face-to-face teams is important. Although our field data provide strong external validity, the cross-sectional design of our study make direct examination of causal relationships difficult. The causal relationships among VRT use, judgment and policy shifts, bias and accuracy, imagery processing, and group cohesion are difficult to disentangle because many of the studied variables are measured simultaneously. Although the strict temporal sequencing of events, and the use of multiple controls for alternative explanations, helps mitigate these concerns, and our use of multiple methods including experiments and interviews provides supportive evidence, these causal concerns cannot be eliminated entirely. Our archival data may also suffer from selection bias because we are unable to capture the entirety of information technologies used by team members and rely on references to these technologies in the group chats. Other studies could design experiments to address these causality and selection bias issues.

Other studies could also examine the potential downsides of persuasive technologies in team settings. For example, if elements such as visualness lead to heuristic (vs. systematic) team decision processes, then an optimal level of visualness, above which declines in team performance are found, may be observed. Similarly, although greater visualness in information technologies may be associated with greater team cohesion, a downside of using such technologies in virtual team settings may be groupthink, in which a team fails to consider a wide range of alternative points of view and decision paths (Furst et al. 1999).

Our study presents initial evidence that VRT use engages imagery processing and leads to greater group cohesion, as shown by language use. Future research could examine other cognitive processes engaged by technologies in team settings and identify those with the largest impact on persuasion and team decision making. Studies could also examine how making VRTs available to virtual teams compares to alternative approaches such as employing computer-mediated communication technologies and group support systems. As virtual teams gain access to increasingly sophisticated and persuasive technologies, understanding how these technologies influence teams in unexpected and intended ways will be important.

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REFERENCES

Al-Saadi J, Szykman J, Pierce RB, Kittaka C, Neil D, Chu DA, Remer L, Gumley L, Prins E, Weinstock L, MacDonald C, Wayland R, Dimmick F, Fishman J (2005) Improving national air quality forecasts with satellite aerosol observations. *Bull. Amer. Meteorological Soc.* 86(9):1249-1261.

Alavi M, Tiwana A (2002) Knowledge integration in virtual teams: The potential role of KMS. *J. Amer. Soc. Inform. Sci. Tech.* 53(12):1029-1037.

Andres HP (2002) A comparison of face-to-face and virtual software development teams. *Team Performance Management*. 8(1):39-48.

Benbasat I, Dexter AS (1985) An experimental evaluation of graphical and color-enhanced information presentation. *Management Sci.* 31(11):1348-1364.

Benbasat I, Dexter AS (1986) An investigation of the effectiveness of color and graphical information presentation under varying time constraints. *MIS Quart.* 10(1):59-83.

Bone PF, Ellen PS (1992) The generation and consequences of communication-evoked imagery. *J. Consumer Res.* 19(1):93-104.

Caiazzo F, Ashok A, Waitz IA, Yim SHL, Barrett SRH (2013) Air pollution and early deaths in the United States. Part I: Quantifying the impact of major sectors in 2005. *Atmospheric Environment*. 79:198-208.

Cappel JJ, Windsor JC (2000) Ethical decision making: A comparison of computer-supported and face-to-face group. *J. Bus. Ethics*. 28(2):95-107.

Card SK, Mackinlay JD, Shneiderman B (1999) *Readings in Information Visualization: Using Vision to Think* (Morgan Kaufmann, San Francisco).

Chao LL, Haxby JV, Martin A (1999) Attribute-based neural substrates in temporal cortex for perceiving and knowing about objects. *Nature Neuroscience*. 2(10):913-919.

Chao LL, Martin A (2000) Representation of manipulable man-made objects in the dorsal stream. *NeuroImage*. 12(4):478-484.

Chung CK, Pennebaker J (2014) Using computerized text analysis to track social processes. Holtgraves TM, ed. *The Oxford Handbook of Language and Social Psychology*. (Oxford University Press, United Kingdom), 219-230.

Cialdini RB (2009) *Influence: Science and Practice*. Pearson, 5th ed. New York.

Cramton CD (2001) The mutual knowledge problem and its consequences for dispersed collaboration. *Organ. Sci.* 12(3):346-371.

Crott HW, Szilvas K, Zuber JA (1991) Group decision, choice shift, and polarization in consulting, political, and local political scenarios: An experimental investigation and theoretical analysis. *Organ. Behav. Human Decision Processes*. 49(1):22-41.

Daft RL, Lengel RH, Trevino LK (1987) Message equivocality, media selection, and manager performance: Implications for information-systems. *MIS Quart.* 11(3):355-366.

Dennis AR, Fuller RM, Valacich JS (2008) Media, tasks, and communication processes: A theory of media synchronicity. *MIS Quart.* 32(3):575-600.

Dennis AR, George JF, Jessup LM, Nunamaker JF, Vogel DR (1988) Information technology to support electronic meetings. *MIS Quart.* 12(4):591-624.

Dennis AR, Wixom BH, Vandenberg RJ (2001) Understanding fit and appropriation effects in group support systems via meta-analysis. *MIS Quart.* 25(2):167-193.

Driskell JE, Radtke PH, Salas E (2003) Virtual teams: Effects of technological mediation on team performance. *Group Dynam.: Theory, Res., and Practice*. **7**(4):297-323.

Durand R (2003) Predicting a firm's forecasting ability: The roles of organizational illusion of control and organizational attention. *Strategic Management J.* 24(9):821-838.

Dye TS, MacDonald CP, Anderson CB, Hafner HR, Wheeler NJM, Chan AC (2003) Guidelines for developing an air quality (ozone and $PM_{2.5}$) forecasting program, EPA-456/R-03-002, Environmental Protection Agency, Research Triangle Park, NC.

Eisenhardt KM (1989) Making fast strategic decisions in high-velocity environments. *Acad. Management J.* 32(3):543-576.
El-Shinnawy M, Vinze AS (1998) Polarization and persuasive argumentation: A study of decision making in group settings. *MIS Quart.* 22(2):165-198.
Emrich CG, Brower HH, Feldman JM, Garland H (2001) Images in words: Presidential rhetoric, charisma, and greatness. *Admin. Sci. Quart.* 46(3):527-557.
Fogg BJ (1998) *Persuasive computers: Perspectives and research directions*. ACM Press, Los Angeles. BOOK
Fogg BJ (1999) Persuasive technologies. *Comm. ACM*. 42(5):26-29.
Fogg BJ (2003) *Persuasive Technology: Using Computers to Change What We Think and Do*. (Morgan Kaufmann, San Francisco).
Friendly M, Franklin PE, Hoffman D, Rubin DC (1982) The toronto word pool: Norms for imagery, concreteness, orthographic variables, and grammatical usage for 1,080 words. *Behav. Res. Methods & Instrumentation*. 14(4):375-399.
Furst S, Blackburn R, Rosen B (1999) Virtual team effectiveness: A proposed research agenda. *Inform. Systems J.* 9(4):249-269.
George JF, Easton GK, Nunamaker Jr JF, Northcraft GB (1990) A study of collaborative group work with and without computer-based support. *Inform. Systems Res.* 1(4):394-415.
Gonzales AL, Hancock JT, Pennebaker JW (2010) Language style matching as a predictor of social dynamics in small groups. *Comm. Res.* 37(1):3-19.
Green MC, Brock TC (2000) The role of transportation in the persuasiveness of public narratives. *J. Personality Soc. Psych.* 79(5):701-721.
Green MC, Brock TC (2002) In the mind's eye: Transportation-imagery model of narrative persuasion. Green MC, Strange JJ, Brock TC, eds. *Narrative Impact: Social and Cognitive Foundations* (Lawrence Erlbaum Associates, Mahwah, NJ), 315-341.
Greene WH (2003) *Econometric Analysis* (Prentice Hall, Upper Saddle River, NJ).
Grèzes J, Decety J (2002) Does visual perception of object afford action? Evidence from a neuroimaging study. *Neuropsychologia*. 40(2):212-222.
Hackman JR, Morris CG (1975) Group tasks, group interaction process, and group performance effectiveness: A review and proposed integration. Berkowitz L, ed. *Advances in Experimental Social Psychology*, Vol. 8 (Academic Press, New York), 45-99.
Hall JV, Brajer V, Lurmann FW (2008) The benefits of meeting federal clean air standards in the south coast and San Joaquin Valley air basins. Accessed September 3, 2008, http://publichealth.lacounty.gov.
Hogarth RM, Gibbs BJ, McKenzie CR, Marquis MA (1991) Learning from feedback: Exactingness and incentives. *J. Experimental Psych.: Learning, Memory, and Cognition*. 17(4):734-752.
Holmes EA, Mathews A, Mackintosh B, Dalgleish T (2008) The causal effect of mental imagery on emotion assessed using picture-word cues. *Emotion*. 8(3):395-409.
Ireland ME, Pennebaker JW (2010) Language style matching in writing: Synchrony in essays, correspondence, and poetry. *J. Personality Soc. Psych.* 99(3):549-571.
Jarvenpaa SL (1989) The effect of task demands and graphical format on information processing strategies. *Management Sci.* 35(3):285-303.
Just MA, Newman SD, Keller TA, McEleney A, Carpenter PA (2004) Imagery in sentence comprehension: An fMRI study. *Neuroimage*. 21:112-124.
Kahneman D (2011) *Thinking, Fast and Slow* (Macmillan, New York).
Keller PA, Block LG (1997) Vividness effects: A resource-matching perspective. *J. Consumer Res.* 24(3):295-304.
Keller PA, McGill AL (1994) Differences in the relative influence of product attributes under alternative processing conditions: Attribute importance versus attribute ease of imagability. *J. Consumer Psych.* 3(1):29-49.

Knight D, Pearce CL, Smith KG, Olian JD, Sims HP, Smith KA, Flood P (1999) Top management team diversity, group process, and strategic consensus. *Strategic Management J.* 20(5):445-465.

Kock N (2004) The psychobiological model: Towards a new theory of computer-mediated communication based on Darwinian evolution. *Organ. Sci.* 15(3):327-348.

Kosslyn SM (1994) *Elements of Graph Design* (W.H. Freeman, New York).

Kosslyn SM, Sukel KE, Bly BM (1999) Squinting with the mind's eye: Effects of stimulus resolution on imaginal and perceptual comparisons. *Memory and Cognition*. 27(2):276-287.

Lahiri K, Teigland C (1987) On the normality of probability distributions of inflation and GNP forecasts. *Internat. J. Forecasting*. 3(2):269-279.

Larkin JH, Simon HA (1987) Why a diagram is (sometimes) worth ten thousand words. *Cognitive Sci.* 11(1):65-100.

Lee AY (2004) The prevalence of metacognitive routes to judgment. *J. Consumer Psych.* 14(4):349-355.

Lee AY, Labroo AA (2004) The effect of conceptual and perceptual fluency on brand evaluation. *J. Marketing Res.* 41(2):151-165.

Ludwig S, de Ruyter K, Mahr D, Wetzels M, Brüggen E, de Ruyck T (2014) Take their word for it: The symbolic role of linguistic style matches in user communities. *MIS Quart.* 38(4):1201-1217.

Lurie NH (2004) Decision making in information-rich environments: The role of information structure. *J. Consumer Res.* 30(4):473-486.

Lurie NH, Mason CH (2007) Visual representation: Implications for decision making. *J. Marketing*. 71(1):160-177.

MacInnis DJ, Price LL (1987) The role of imagery in information processing: Review and extensions. *J. Consumer Res.* 13(4):473-491.

Magnussen S, Helstrup T (2007) *Everyday Memory* (Psychology Press, Hove, England).

Majchrzak A, Malhotra A, John R (2005) Perceived individual collaboration know-how development through information technology-enabled contextualization: Evidence from distributed teams. *Inform. Systems Res.* 16(1):9-27.

Martindale C (1975) *Romantic Progression: The Psychology of Literary History* (Hemisphere, Washington, D.C.).

Martins LL, Gilson LL, Maynard MT (2004) Virtual teams: What do we know and where do we go from here? *J. Management*. 30(6):805-835.

Mellet E, Bricogne S, Crivello F, Mazoyer B, Denis M, Tzourio-Mazoyer N (2002) Neural basis of mental scanning of a topographic representation built from a text. *Cerebral Cortex*. 12(12):1322-1330.

Miranda SM, Saunders CS (2003) The social construction of meaning: An alternative perspective on information sharing. *Inform. Systems Res.* 14(1):87-106.

Montoya-Weiss MM, Massey AP, Song M (2001) Getting it together: Temporal coordination and conflict management in global virtual teams. *Acad. Management J.* 44(6):1251-1262.

Neidell M (2010) Air quality warnings and outdoor activities: Evidence from Southern California using a regression discontinuity design. *J. Epidemiology and Community Health*. 64(10):921-926.

O'Craven KM, Kanwisher N (2000) Mental imagery of faces and places activates corresponding stiimulus-specific brain regions. *J. Cognitive Neuroscience*. 12(6):1013-1023.

O'Keefe DJ (1990) *Persuasion: Theory and Research* (Sage, Newbury Park, CA).

Oinas-Kukkonen H, Harjumaa M (2009) Persuasive systems design: Key issues, process model, and system features. *Comm. Association Inform. Systems*. 24(1, Article 28):485-500.

Paivio A, Csapo K (1973) Picture superiority in free recall: Imagery or dual coding? *Cognitive Psych.* 5(2):176-206.

Pandey AV, Manivannan A, Nov O, Satterthwaite M, Bertini E (2014) The Persuasive Power of Data Visualization. *IEEE Transactions on Visualization and Computer Graphics*. 20(12):2211-2220.

Pennebaker JW, Booth RJ, Francis ME (2007) *Linguistic Inquiry and Word Count (LIWC 2007)*, Austin, TX.

Petrova PA, Cialdini RB (2008) Evoking the imagination as a strategy of influence. Haugtvedt CP, Herr P, Kardes FR, eds. *Handbook of Consumer Psychology*. (Routledge, New York).
Powell A, Piccoli G, Ives B (2004) Virtual teams: A review of current literature and directions for future research. *The DATA BASE for Advances in Inform. Systems*. 35(1):6-36.
Sarker S, Sarker S, Chatterjee S, Valacich JS (2010) Media effects on group collaboration: An empirical examination in an ethical decision-making context. *Decision Sci.* 41(4):887-931.
Schmidt JB, Montoya-Weiss MM, Massey AP (2001) New product development decision-making effectiveness: Comparing individuals, face-to-face teams, and virtual teams. *Decision Sci.* 32(4):575-600.
Schwarz N (2004) Metacognitive experiences in consumer judgment and decision making. *J. Consumer Psych.* 14(4):332-348.
Seyranian V, Bligh MC (2008) Presidential charismatic leadership: Exploring the rhetoric of social change. *The Leadership Quart.* 19(1):54-76.
Sherman SJ, Cialdini RB, Schwartzman DF, Reynolds KD (1985) Imagining can heighten or lower the perceived likelihood of contracting a disease. *Personality Soc. Psych. Bull.* 11(1):118-127.
Sia CL, Tan BCY, Wei KK (2002) Group polarization and computer-mediated communication: Effects of communication cues, social presence, and anonymity. *Inform. Systems Res.* 13(1):70-90.
Simons HW (1976) *Persuasion: Understanding, Practice, and Analysis*. Addison-Wesley, Reading, MA.
Sloman SA (1996) The empirical case for two systems of reasoning. *Psych. Bull.* 119(1):3-22.
Sproull L, Kiesler S (1986) Reducing social-context cues: Electronic mail in organizational communication. *Management Sci.* 32(11):1492-1512.
Stigliani I, Ravasi D (2012) Organizing thoughts and connecting brains: Material practices and the transition from individual to group-level prospective sensemaking. *Acad. Management J.* 55(5):1232-1259.
Straub D, Karahanna E (1998) Knowledge worker communications and recipient availability: Toward a task closure explanation of media choice. *Organ. Sci.* 9(2):160-175.
Tan BCY, Wei KK, Watson RT, Clapper DL, McLean ER (1998) Computer-mediated communication and majority influence: Assessing the impact in an individualistic and a collectivistic culture. *Management Sci.* 44(9):1263-1278.
Thomas JJ, Cook KA (2005) *Illuminating the Path the Research and Development Agenda for Visual Analytics* (IEEE Computer Society Press, Los Alamitos, CA).
Todd P, Benbasat I (1999) Evaluating the impact of DSS, cognitive effort, and incentives on strategy selection. *Inform. Systems Res.* 10(4):356-374.
Tormala ZL, Petty RE, Briñol P (2002) Ease of retrieval effects in persuasion: A self-validation analysis. *Personality Soc. Psych. Bull.* 28(12):1700-1712.
Von Glinow MA, Shapiro DL, Brett JM (2004) Can we talk, and should we? Managing emotional conflict in multicultural teams. *Acad. Management Rev.* 29(4):578-592.
Weldon MS, Bellinger KD (1997) Collective memory: Collaborative and individual processes in remembering. *J. Experimental Psych: Learning, Memory, and Cognition*. 23(5):1160-1175.
Yoo Y, Alavi M (2001) Media and group cohesion: Relative influences on social presence, task participation, and group consensus. *MIS Quart.* 25(3):371-390.
Zhang D, Lowry PB, Zhou L, Fu X (2007) The impact of individualism--collectivism, social presence, and group diversity on group decision making under majority influence. *J. Management Inform. Systems*. 23(4):53-80.
Zhang X, Venkatesh V, Brown SA (2011) Designing collaborative systems to enhance team performance. *J. Association Inform. Systems*. 12(8):556-584.
Zigurs I, Poole MS, DeSanctis GL (1988) A study of influence in computer-mediated group decision making. *MIS Quart.* 12(4):625-644.

Table 1. Means, Standard Deviations, and Correlations

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Bias	7.03	22.05										
2. Inaccuracy	16.09	16.62	.75***									
3. Forecast Shift	.12	.77	.03	.01								
4. Up-Down Shift	.02	.26	-.04	-.04	.54***							
5. Technology Visualness	33.26	43.43	-.09*	-.06	.12**	.12**						
6. Corrected Visualness	-1.78	1.81	-.09*	-.06	.12**	.12**	1.00***					
7. Lack of Consensus	31.90	34.65	-.06	-.03	.13***	.04	.11**	.11**				
8. YO	.23	.42	.06	-.02	.07	.13***	.01	.01	-.15***			
9. OR	.05	.21	.04	-.01	.22***	.26***	.14***	.14***	.05	-.12***		
10. Weekday	.72	.45	-.06	-.03	-.01	.00	.12**	.12**	-.01	.04	.03	
11. Holiday	.02	.14	.11**	.10**	-.10**	-.07	.04	.04	-.06	.07	.04	.09*
12. Team Size	4.91	1.29	-.06	-.06	-.05	-.04	.15**	.15***	-.02	.01	.01	.22***
13. Expertise Diversity	.58	.14	.03	-.01	-.09*	.00	-.13**	-.13***	-.04	-.03	-.03	-.08*
14. Location Diversity	.45	.08	.03	-.01	.02	-.02	.12**	.12**	.07	-.08	.00	.13***
15. Gender Diversity	.27	.16	-.06	-.01	-.13***	-.10**	-.01	-.01	.05	-.07	.00	.14***
16. Participation	.93	.12	.03	-.01	.06	.06	-.03	-.03	.00	.11**	-.01	.03
17. Information Amount	11220.76	65702.20	.02	.03	-.01	.01	.26**	.26***	-.03	-.06	-.03	.03

	11	12	13	14	15	16
12. Team Size	-.01					
13. Expertise Diversity	.07	.35**				
14. Location Diversity	.02	.33**	.23***			
15. Gender Diversity	.06	.30***	-.04	.07		
16. Participation	.02	.00	-.06	-.03	-.07	
17. Information Amount	.04	.03	.01	.06	-.02	-.04

N = 457. *** $p < .01$; ** $p < .05$; * $p < .10$. Forecaster and month dummies are included.

Table 2. Antecedents of VRT Use (Technology Visualness Corrected for Chance)

	Model 1 (Base Model)		Model 2 (Expanded Model)	
Independent Variables	Coefficient	t-value	Coefficient	t-value
Intercept	-3.802***	-3.96	-3.667***	-3.78
Weekday	.103	.55	.167	.89
Holiday	.973*	1.96	.963*	1.88
Team Size	-.104	-.36	-.081	-.28
Expertise Diversity	-.032	-.03	-.150	-.16
Location Diversity	1.975**	2.32	1.579*	1.80
Gender Diversity	-2.210	-1.56	-2.525*	-1.77
Participation	-.383	-.59	-.361	-.55
Lack of Consensus			.002	.69
YO			-.405*	-1.71
OR			.345	.84
Lack of Consensus × YO			.012***	2.90
Lack of Consensus × OR			.007*	1.78
R^2	.20		.22	
F	5.75		8.56	

N = 457. *** p <.01, ** p < .05, * p < .10. Forecaster and month dummies are included.

Table 3. Technology Visualness (Corrected for Chance) and Persuasion

	Model 3 (Tobit model)		Model 4 (Multinomial logistic model)			
	ForecastShift		*UpDownShift* = −1		*UpDownShift* = +1	
Independent Variables	Coefficient	t-value	Coefficient	z-value	Coefficient	z-value
Intercept	-.036	-.15	-37.264	.00	-9.572**	-2.00
Weekday	.003	.07	-2.439***	-2.81	-1.022*	-1.81
Holiday	-.159	-1.08	5.137**	2.51	-19.358	.00
Team Size	-.039	-.58	-1.002	-.65	-.818	-.86
Expertise Diversity	.246	1.13	-9.622*	-1.76	6.007	1.22
Location Diversity	.153	.61	1.992	.25	-4.351	-1.19
Gender Diversity	-.384	-1.16	-3.917	-.51	1.313	.25
Participation	.152	1.13	1.615	.42	6.108*	1.76
Information Amount	.000	-1.34	.000	-.45	.000	-.25
Corrected Visualness	.026**	2.45	-.056	-.21	.359**	2.24
Log likelihood	-242.82		-94.47			
χ^2	35.15		76.71			

N = 457. *** p <.01, ** p < .05, * p < .10. Reference category is *UpDownShift* = 0
Forecaster and month dummies are included.

Table 4. Technology Visualness (Corrected for Chance) and Team Performance

	Model 5		Model 6	
	Percent Error of Inaccuracy		Percent Error of Bias	
Independent Variables	Coefficient	t-value	Coefficient	t-value
Intercept	18.583	1.54	-11.191	-.68
Weekday	-1.160	-.66	-2.946	-1.26
Holiday	11.089	1.5	18.513**	2.49
Team Size	-4.643*	-1.93	-7.312**	-2.16
Expertise Diversity	-4.037	-.46	-4.531	-.33
Location Diversity	1.799	.20	10.792*	.72
Gender Diversity	16.172	1.22	11.050	.59
Participation	-4.055	-.44	4.972	.44
Information Amount	.000	.95	.000	1.57
Corrected Visualness	-.567	-1.25	-1.400**	-2.23
R^2	.09		.10	
F	1.80		1.91	

N = 457. *** p <.01, ** p < .05, * p < .10. Forecaster and month dummies are included.

Figure 1. VRT Example: 850 mb Weather Contour Map

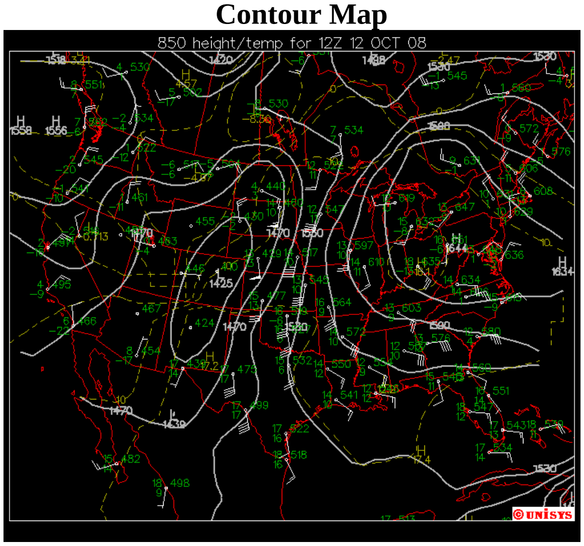

Figure 2. Non-VRT Example: Weather Diagnostics Tool

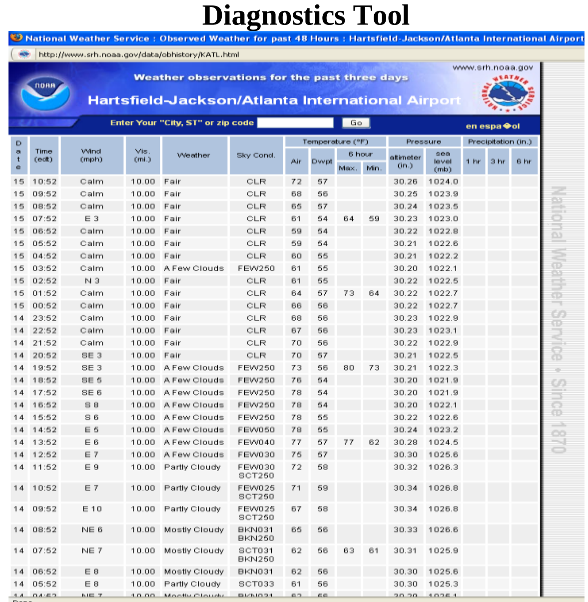

Figure 3. Example of Daily Chat Room Discussion

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

Note: In this example, the smog forecasting team refers to three VRTs (NAM, NGM, and NAM-bufkit) to help them make a prediction for July 19, 2008.