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Putting on the Thinking Cap: Using NeuroIS to Understand Information Processing Biases in Virtual Teams

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Abstract: Virtual teams are increasingly common in today's organizations, yet they often make poor decisions. Teams that interact using text-based collaboration technology typically exchange more information than when they perform the same task face-to-face, but past results suggest that team members are more likely to ignore information they receive from others. Collaboration technology makes unique demands on individual cognitive resources that may change how individual team members process information in virtual settings compared to face-to-face settings. This experiment uses electroencephalography, electrodermal activity, and facial electromyography to investigate how team members process information received from text-based collaboration during a team decision-making process. Our findings show that information that challenges an individual's prediscussion decision preference is processed similarly to irrelevant information, while information that supports an individual's prediscussion decision preference is processed more thoroughly. Our results present neurological evidence for the underlying processes of confirmation bias in information processing during online team discussions.

Key words and phrases: collaboration technology, electroencephalography, information processing bias, NeuroIS, virtual teams.

The prevalence of virtual teams has increased over the past decade, and they are commonplace in today's organizations [34]. Virtual teams communicate via different forms of information and communication technologies (ICTs) [90], such as videoconferencing, e-mail, online chat, and instant messaging. These different tools vary in richness and synchronicity, providing flexibility in the way virtual teams communicate [24]. Previous research has examined the role of individual cognition in virtual team interactions and how it can affect performance [25, 42].

Text-based communication, such as instant messaging, chat, e-mail, and discussion forums, is common for virtual teams because it provides many benefits over face-to-face communication, such as elimination of production blocking, and provision of a meeting memory [75], but also introduces other issues. Studies have shown that virtual teams using text-based communication share more information than their face-to-face counterparts [22]. Yet despite having more information, these teams do not necessarily reach better decisions than face-to-face teams [22]. Research suggests that one reason for this poor decision making is that team members do not pay attention to the information they receive from others, but instead engage in "multiple monologues" [23] in which they focus instead on talking about what they know instead of considering the information they receive from others [22, 27, 47].

Previous research has also suggested cognitive biases that may affect information processing [70], such as escalation of commitment, anchoring and adjustment, confirmation bias, and sunk-cost fallacy [49]. We focus on confirmation bias, which is the tendency to search for or interpret information in a way that confirms one's preconceptions [52]. Confirmation bias might manifest in virtual team interactions by team members attending only to information that conforms to beliefs they had *before* entering the virtual chat room, thus limiting the effectiveness of the virtual team interaction. Since neuroimaging tools allow researchers to examine changes in cognition, they can be used to uncover which biases are most pronounced in virtual teams.

This paper reports on a study that uses two techniques from NeuroIS [30] to investigate how members of virtual teams process the information they receive from others to better understand where the breakdowns in processing text-based communication occur. First, we use electroencephalography (EEG) to measure the cognitive response to informational statements that present new facts about the decision alternatives. Second, we use changes in electrodermal activity (EDA) and facial electromyography (EMG) to measure the emotional response to this information. Both cognitive and emotional measures are used because both responses to information are important components of the decision-making process [54]. We studied the participants' responses to five types of information: facts that supported their preference, facts that challenged their preference, normative statements that challenged their preference, normative statements that supported their preference, and irrelevant information.

Theoretical Framework

Decision making is an arduous process of sifting through relevant and irrelevant information to determine the important information [96]. The decision maker is often surrounded with conflicting information [96]. Team decision making adds one more layer of complexity because each team member needs to consider the preferences of others as well as the facts that he or she knows [86]. When other team members hold different preferences, it suggests that they know different information or have interpreted the same information in a different manner [85].

Decision Making and Confirmation Bias

The decision making process is a dynamic one involving multiple decision factors. There are three distinct stages in the decision-making process: the predecision stage, the decision stage, and the postdecision stage [96]. We focus on the first two. The predecision stage involves gathering information about the alternatives [96]. Teams are often formed because they have access to more information than any one person acting alone [39]. Because teams usually have members from different parts of the organization, with different levels of experience, or from different functional areas, they enable a deeper pool of knowledge and experience to be applied to the decision, which should result in better decisions [39]. Past research has shown that, on average, teams make better decisions than individuals, even when they are comprised of team members with relatively homogeneous backgrounds, perhaps because they are less likely to make major errors [56].

The net result of the dynamic processes associated with group decision making is what Stasser [85] has called a "hidden profile" task. Each team member knows some baseline information that is known to all the team members, which is often called "common information" [22]. Each team member also usually knows some "unique information" that is known only to them. This combination of information typically leads each team member to form initial prediscussion preferences about the decision alternatives. Because these prediscussion preferences are based on a mixture of common and unique information, it is not unusual for individual team members to develop different preferences prior to team discussion.

During the decision stage, team members discuss alternatives (face-to-face or virtually). During this process, they share information and their preferences for the alternatives. Thus, the information that team members contribute to and receive from the discussion can be organized into two distinct categories [78]. The first is factual information about the alternatives. Factual information is devoid of opinion [55]. It simply states the facts and leaves interpretation to the receiver. The second category is normative information about the preferences of the contributor. Normative information states which alternative(s) the contributor prefers, without providing reasons [55].

Communication, whether spoken or typed, contains a mixture of factual information and normative information, sometimes in the same phrase. But viewed in its purest form, communication falls into one of these two categories. When team members engage in discussion they receive a mixture of both. It is the combination of factual and normative information that team members contribute and consider that shapes the team decision.

Because most teams have a mixture of common and unique information, team members often receive information they already know as well as new information. This new information—information not considered in the prediscussion stage—should be what a team member focuses on because it is new and not yet considered [22]. Such new information may support or challenge the prediscussion preferences that a team member has developed. In theory, new information that challenges prediscussion preferences is the most important and should receive the most attention because it has the greatest potential to change decisions [83, 95].

How team members respond to the new information they receive from others, especially information that challenges their prediscussion preferences, is often critical to the quality of the decisions that the team makes. These prediscussion preferences that team members form have the potential to bias the decision-making process [57, 72, 96]. People are generally biased toward their initial decisions [57, 72] to avoid cognitive dissonance [31, 53]. They do not feel comfortable holding two opposing thoughts [17, 31] so, to prevent this, they often seek to support their prediscussion preferences rather than challenge them. This has been shown to be the case even if team members believe that they do not do this [72]. This bias often plays out in two forms. The first is selective information search [4, 84], in which people search for information that supports their initial decisions [4, 57]. Selective information search leads to biased information being made available to the decision makers such that most of the information gathered supports prediscussion preferences.

Confirmation bias, the second form of bias, is the tendency to ignore information that challenges one's decision preferences [4, 61]. When decision makers uncover information that challenges their preferences, they resolve the cognitive dissonance by ignoring the contradictory information [4, 61]. This leads to the biased interpretation of new information such that information that supports prediscussion preferences is considered while information that challenges those preferences is ignored [4]. Thus, the net effect of gathering new information is to reinforce the existing preferences rather than to help decision makers find better solutions, even when new information both supports and challenges existing preferences. This hurts decision quality if the initial decision preferences are incorrect [53].

Most of the research on bias in decision making has focused on individual decision making, not team decision making. One would hope that involving other people in the decision process, each of whom may bring their own—and potentially different—biases to the discussion, might overcome some of the selective information search and confirmation bias observed in individual decision making. Unfortunately, selective information search also has been observed in teams that meet face-to-face to make decisions [53]. Stasser and colleagues have published many studies that examine face-to-face decision-making teams and have repeatedly found that individual team members engage in selective information search by focusing the discussion on common information known to all team members and failing to share the information that only they possess [85, 86]. As a result, team decisions are often poor.

ICT has the potential to change this pattern because it is designed to change the way team members interact by providing parallelism, shared memory, occasional anonymity, and other features [75]. Research on teams using ICT with synchronous text-based communication shows that team members share more unique information [22, 27]. In other words, text-based communication helps teams overcome the selective information search bias that is commonly observed in face-to-face teams.

Paradoxically, this same research shows that teams do not make better decisions because individuals fail to integrate the information they receive from others into their decision processes [27]. The information is shared and present in the discussion, but team members do not seem to process it when making decisions. It is as though team members are engaged in "multiple monologues" [23] by typing their own information, rather than engaging in true dialogue that considers the information and opinions that other team members contribute. There is even some evidence to suggest that text-based discussion actually intensifies this problem compared to face-to-face teams [22, 47].

Yet despite more than a decade of research on this problem, we still do not understand the underlying mechanism by which this failure to process new information works. Such understanding is vital as it is the first step to designing interventions to mitigate confirmation bias. There are two common theoretical positions proposed to explain the phenomenon. One line of reasoning is based on the concept of information overload [42]. Text-based discussions contain more information than face-to-face discussions, because parallelism is inherent in ICT-based discussions [22, 38]. This increase in information can overload a limited cognitive system, resulting in a lack of attention paid to the information presented. Theories of limited capacity applied to mediated message processing (e.g., [63]) propose that cognitive resources are allocated purposefully—based on personal salience—and reflexively due to evolved mechanisms of information intake such as the orienting response [65, 79]. However, because of the limited availability of cognitive resources at any one time, cognitive overload can occur [63]. When this happens in an information-rich environment such as ICT-based chats, team members are unable to pay attention to information even though it is clearly presented. As a result, important details are not processed and poor decision making occurs.

The work of Heninger et al. [42] on dual task interference contributes to this first explanation. When participants watched a text-based discussion, they remembered more information (and made better decisions) than when they participated in the discussion and contributed the information they knew. The need to contribute information required additional cognitive resources and thereby interfered with the allocation of cognitive resources to the task of processing the information received from others. Again, decision performance was reduced.

Under this first interpretation, the failure to process new information is subconscious and due to a lack of cognitive resources. Parallelism, information overload, and dual task interference prevent participants from both reading and contributing at full effectiveness, so participants choose to focus on contributing what they know. In other words, both the information-rich nature of the ICT and the desire to contribute one's own thoughts combine to drain the limited cognitive resources available to process the discussion task. This prevents the careful consideration of others' thoughts, leading to incomplete and biased processing and resulting in poor decisions.

An alternative line of reasoning is that team members do in fact have sufficient resources available to read and process the information they receive from other team members, but they disregard information that disagrees with their preferences. Research indicates that information contained in preference-challenging statements is at least initially processed. This information can lead to cognitive dissonance, often shown to lead to a negative emotional reaction. Theories of human emotion, for example, suggest that humans have evolved survival mechanisms to devote more attention to negative stimuli [10, 12, 95]. This is supported by media research that suggests that negative messages are more memorable than positive ones [64, 73].

Under this second theoretical view, all information—including that which challenges an individual's preferences—is initially processed. However, due to cognitive dissonance, team members discount information that challenges their initial prediscussion preferences and choose not to integrate it into their decision framework. This is supported by the work of Fiske and Taylor [32], who found that individuals prefer to dwell on positive thoughts. Under this interpretation, confirmation bias is conscious and a result of cognitive dissonance (although team members may or may not be aware of the impact of the bias). In this case, it is the prediscussion preferences that shape how new information is interpreted and whether that information is accepted and used in making the final decision.

These two alternatives present different underlying explanations for the lack of information processing and poor decision making among ICT teams. The need for data to illuminate the actual mechanisms is real, as each implies different approaches to designing ICT to mitigate poor decision making. Recent advances in NeuroIS offer the possibility of looking "inside the black box" of how team members process information from others [30, 79].

NeuroIS

NeuroIS is the application of cognitive neuroscience methods in the information systems (IS) field and provides an opportunity to reexamine and address existing problems through a new methodological lens [30, 80]. The application of these methods may provide greater understanding of existing IS effects as well as enable the innovative integration of cognitive neuroscience theories, providing extensions to existing IS theories. Cognitive neuroscience employs a diverse body of methodologies that allows researchers to "open up" the black box of the brain to further understanding of human cognition and emotional processing. Central to these methodologies are various measures of cortical activation, including neuroimaging techniques such as functional magnetic resonance imaging (fMRI) and measures of the neurophysiological activity of the brain with electroencephalography (EEG) [30]. NeuroIS also encompasses peripheral psychophysiological measures such as EDA and EMG [80]. Both central and peripheral measures are conceptualized as physiological correlates of neurological and psychological activity in the brain [13, 79]. These techniques, along with others in the NeuroIS arsenal, may provide new insights into how humans process and react to information in the environment, including information delivered by information technologies [30, 80].

In this study, we use NeuroIS techniques to gain an understanding of how individual team members process the information they receive from a text-based discussion during team decision making. Our focus is on individuals working within a team context. Both cognition and emotion are important in decision making, so we examine how individuals respond to the factual and normative information they receive from others using both a cognitive and emotional perspective. We begin with cognition (EEG) and then turn to emotion (EDA, facial EMG).

Cognitive Responses to Information

EEG is a psychophysiological measurement of postsynaptic electrical potentials on the surface of the scalp [37]. Electrodes are placed at specific locations of the scalp to collect the summation of synchronized activity from underlying pyramidal neurons lying near the surface of the cortex. The measure at each electrode location is then compared to a reference electrode located elsewhere on the scalp [40]. The recorded oscillations of brain activity at each electrode are complex waveforms that can be decomposed into simple waveforms of different periodicity at varying amplitudes. EEG researchers often are interested in five frequency bands: delta (< 4 Hz [hertz]), theta (4–8 Hz), alpha (8–13 Hz), beta (13–20 Hz), and gamma (> 20 Hz) [40]. In this study we focus on the alpha band because of the inverse relationship between alpha frequency amplitude and attention, wherein lower levels of alpha represent higher levels of cognitive processing. This phenomenon is referred to as "alpha blocking" [2, 79].

We began developing hypotheses by deconstructing the cognitive processes associated with text-based team discussion to identify regions where alpha blocking would be expected. Information is presented visually via text displayed on a computer screen. If an individual observes and pays attention to incoming textual information, decreases in alpha could be expected in the occipital region of the brain, known to pertain to initial processing of visual stimuli [6]. Initial high-level categorization of the information occurs in this region (i.e., "this is a word" versus "this is a face") [6]. Language-related information is relayed to language-processing regions such as Wernicke's and Broca's areas for assessments of relevance [82, 93]. If information is perceived as irrelevant, activation of these regions is reduced [5, 9]. For this reason, we believe that messages perceived as irrelevant will not receive as much processing in the temporal and frontal regions of the brain as relevant information.

Following processing by the visual and language areas, relevant information will be passed along for further processing to the frontal cortex where the working memory regions of the brain are located, while irrelevant information will not [5, 9]. Working memory plays a central role in cognition [5]. It encapsulates both what many consider "short-term memory" and attention. Therefore, working memory is pivotal for both information processing and decision making, responsible for encoding information from the environment and retrieving information from long-term memory in order to make sense of it [5, 94]. A useful computer analogy for understanding working memory is that it represents the brain's RAM (random access memory), storing information currently undergoing processing but limited in its capacity [28]. Working memory is located in the frontal areas of the cortex, namely, the Dorsolateral Prefrontal Cortex (DLPFC) [29]. Changes in activity in the DLPFC can indicate changes in working memory load and attention [18, 92]. In EEG, attenuation of the alpha rhythm over the DLPFC indicates increases in working memory load [36]. When the brain is at rest, alpha rhythms result from the synchronization of underlying neural activity, which is indicative of an "idling" process. Better cognitive performance has been associated with increased activity in the DLPFC [48].

We are interested in how factual information (i.e., facts about alternatives) and normative information (statements of team members' preferences for alternatives) are processed, and if this processing differs depending on whether the information supports or challenges the individual's prediscussion preferences. We argued that there were two plausible explanations for why members of virtual teams engaged in text discussions fail to consider the information they receive from other team members when they make decisions. The pattern of brain activity when new information is received is likely to be quite different under each of the two explanations.

Under the first explanation, team members experience information overload due to the dual task interference in a virtual environment and they fail to attend to the information from others, instead focusing on contributing what they know. If this is the case, then we would expect to see little change in activation in the visual and language portions of the brain when new information appears on the screen. The brain is engaged in other cognitive activities, and thus is unable to process the new information very extensively.

Under the second explanation, individuals see and process the new information. The brain regions associated with visual and language processing will experience increased activity upon information onset and will pass the information to the working memory area of the brain for further processing. When it reaches these frontal regions, new information that challenges the individual's prediscussion preferences, whether factual information or normative in nature, is processed in the same manner as irrelevant information. If this is the case, then we would expect to see significant changes in activation in the visual and language portions of the brain when new information appears on the screen, whether factual or normative. However, we would expect to see differential activity in the working memory areas of the brain depending on the nature of the information; information (whether factual or normative) that challenges the prediscussion preferences would be treated in the same manner as irrelevant information and trigger less activity than information that supported the prediscussion preferences.

Both explanations have supporting evidence from empirical behavioral research and are plausible. Nonetheless, we believe that the second explanation is more likely; information overload is possible, but the information shared in most team discussions do not require large amounts of cognitive resources to process. It is more plausible that confirmation bias leads team members to discount information that challenges their prediscussion preferences. Thus,

Hypothesis 1: When members of virtual teams receive relevant text-based information from other team members, they will attend to it and consider it. Specifically,

Hypothesis 1a: Areas of the brain that pertain to contextual information processing will show increased activity when factual or normative information is received compared to irrelevant information.

Hypothesis 1b: Areas of the brain that pertain to language processing will show increased activity when factual or normative information is received compared to irrelevant information.

Hypothesis 2: When members of virtual teams receive text-based information from other team members, they will discount factual and normative information that challenges their prediscussion preferences. Specifically,

Hypothesis 2a: Areas of the brain that pertain to working memory will show increased activity when preference-supporting factual or normative information is received compared to irrelevant information.

Hypothesis 2b: Areas of the brain that pertain to working memory will not show increased activity when preference-challenging factual or normative information is received compared to irrelevant information.

Emotional Responses to Information

Emotion has been conceptualized and investigated in two general, compatible ways. One is to approach the study of emotion with an eye to specific, identifiable discrete emotions [33]. Many discrete emotion researchers focus on a handful of basic or universal emotions such as fear, joy, anger, and disgust [69]. A second approach to emotional response, and the one utilized in this study, is to view any discrete emotion as being comprised of different amounts of core underlying dimensions [10, 12]. Most emotional research of this type has identified three such dimensions: arousal/excitement, valence, and dominance, with most of the statistical variance in responses across emotional situations being accounted for by the first two [11].

Under a dimensional conceptualization of emotional response, there are three primary ways of operationalizing arousal and valence: through observation of behaviors, self-report, and physiological response [11]. This study relied on the latter, conceptually defining arousal as the level of excitement experienced during specific moments in time as the participant was involved in the text-based discussion, indicated via activation of the sympathetic nervous system. Arousal was quantified using EDA; specifically, the skin conductance level measured off the palm of the participant's nondominant hand. Valence was conceptually defined as the extent to which the participant felt positive or negative during specific moments in the text-based discussion. This was operationally defined using activation or deactivation of the corrugator supercilli muscle, located just above the subject's left eyebrow, to indicate negative or positive response, respectively.

With these two measures of the key underlying dimensions of emotion we can consider what participant reactions would be according to the theoretical explanations for poor decision making in virtual teams. If cognitive overload is the cause, then little emotional response is expected because the processing of information is curtailed. We would predict increased arousal and negative valence early in the online discussion session as the participant tried hard to thoroughly complete the task. Eventually, however, both excitement and valence would be expected to show little response to the onset of information either supporting or disagreeing with the participant's initial position.

As indicated above, however, it is our contention that the amount of cognitive resources required during a text-based discussion falls below the level of overload, even given the added resource requirements of any "multiple monologues" the participant may be rehearsing and/or generating. Therefore, the hypotheses we make are based on the second theoretical position, that much of the information presented in the text-based discussion is at least initially processed and only statements that agree with the participant's initial decision move from initial perceptive processing to deeper levels of processing in working memory.

Research in the processing of emotional text shows increased activation of the corrugator muscle in response to the onset of negatively valenced text and significant deactivation in response to positively valenced text [67]. We expect that differences in physiological valence responses most likely occur immediately after any information is received and initially processed—both information that supports the participant's preferences and that which challenges it. Electromyographic measures are comparatively rapid in response to external stimuli, with onset latencies as quick as 20–40 milliseconds (ms) [87]. We predict that preference-challenging information will be processed only in very early stages of cognitive evaluations, and only information that supports the prediscussion positions of the participant will be passed on to working memory, so any response to the contradictory information is expected to be seen quite early in the processing sequence and only in the corrugator EMG response. Therefore,

> *Hypothesis 3: During early processing of information, there will be significantly larger negative responses—indicated by greater activation of the corrugator muscle group—in response to information challenging the individual's initial decision compared to information supporting his or her initial decision.*

The arrival of new textual information onscreen has been found to elicit orienting responses when the information is part of an ongoing storyline [89] or if the information is particularly pertinent to the receiver [66]. Therefore, we expect the onset of statements in this discussion to trigger orienting and the accompanying initial increase in arousal. However, only statements that are in support of the participant's prediscussion preferences are expected to be further processed in working memory. Past research has associated activity in working memory with greater arousal levels indexed by increases in EDA [7, 50]. Skin conductance response to external stimuli has a comparatively slow onset latency of 1,000–3,000 ms [19]. The combination of time required to further process the information coupled with the long latency window for the skin conductance response leads us to expect evidence for this increase in arousal later on. Therefore,

> *Hypothesis 4: During later processing of information, there will be significantly greater arousal—indexed by more skin conductance activity—in response to information supporting the individual's initial decision compared to information challenging his or her initial decision.*

Method

Our goal in this study was to understand how individual team members respond to new information they receive from other team members during a text-based ICT discussion. Therefore, the unit of analysis was the individual, not the team. Given this focus, having real participants interact with each other and measuring the data at the individual level would introduce large error variance because each team discussion is likely to be different. Therefore, we used a simulator (see [35, 42, 47]) designed to look and act like a real instant messenger tool. The study participant could type comments in the simulator and see them contribute to the discussion. While the simulator seemed to present the study participant with comments from others, they were in fact part of a standardized script. The simulator acted like a set of automated confederates, and the participants engaged in a discussion [42]. As far as the participant was concerned, the team's task was to discuss decision alternatives. However, the final decision would be made at the individual level (i.e., after the discussion concluded the individual would come to a postdiscussion decision). Therefore, the purpose of the team discussion was not to reach consensus, but rather to discuss the decision alternatives. Prior research has used simulators to replicate the predecision phase and evaluation of decision alternatives (see [42]). The simulator emulated a discussion of the decision-related information, in which the participants readily interacted. So as to not bias the outcomes, the participants were not informed that they were using a simulator until they were debriefed at the end of the experimental session.

Participants

The participants were undergraduate students from a large state university who received course credit for their time. Fifty-four participants took part in the experiment, but ten were omitted from the analysis because they failed the manipulation check (described below), leaving a total of 44 participants. This is well above the 20–30 subjects used in many EEG studies that utilize a within-subjects design [58]. The final sample consisted of 15 males and 29 females. Thirty-six of the subjects were right-handed, 7 were left-handed, and 1 was ambidextrous.

Task

The task was a hidden profile decision-making task to select three of five student applicants to admit to the university. This task was based on one used extensively in prior research (e.g., [22, 81]). The task environment is familiar to the participants, each of whom has successfully navigated the university entrance process and understands the task information (e.g., GPA [grade point average], SAT). The version of the task we used was validated by the admissions office at the university where the experiment was conducted to ensure that its information was appropriate.

The task had two parts. First, the participant was given incomplete information about the five applicants and asked to make an initial decision of which three to admit. This corresponds to the predecision stage commonly encountered in decision making. The second task was the simulated discussion. The participant was informed that he or she would work in a team with four other participants using a text-based discussion tool to discuss the information and would later be asked to provide a second individual decision that could be the same or different from his or her initial decision. The participants were informed that each team member had received incomplete information. Some common information was known to all of the team members but each member had unique information that was known only to him or her, and that it was important to share this unique information and consider the new information contributed by others in order to reach a good decision.

As noted earlier, the participants did not actually interact with the other team members. Instead they used a team simulator that played a 12-minute prepared script. Like most text-based discussion tools, the simulator provided two onscreen windows. The top window displayed the comments from "other team members" and the bottom window enabled the participants to type their own comments (which were then displayed in the top window with the other comments). The participants were told that the other discussion participants were in different locations across the campus, and not with them in the research lab, because we were not collecting physiological data from them.

Independent Variable

The independent variable was the nature of the information contained in the simulator script displayed to the participants. The scripts were written to closely match the transcripts of discussions from student teams that had performed this task in prior experiments [42]. The script was extensively pilot tested and refined to ensure that both the content and pacing of comments resembled a typical student team discussion for the task.

The script was designed to contain five types of information contained in 63 target statements. Sixteen target statements contained factual information that supported the participant's prediscussion decision preference and 16 target statements contained factual information that challenged the participant's prediscussion decision preference (e.g., Don had one of the highest GPAs). We recorded each participant's prediscussion choice so we could cross-check it against the target statements to ensure that preference-supporting and preference-challenging information was coded appropriately. Eight target statements contained normative information that supported the participant's prediscussion decision preference and eight contained normative information that challenged it (e.g., I like Angela). Fifteen target statements contained irrelevant information designed to provide a baseline against which we could compare the other four types of information (e.g., I'm hungry). The irrelevant information was drawn from transcripts of teams that had performed this task in other experiments, so it is common in team discussions.

Dependent Variables

Our dependent variables were cortical attention, autonomic arousal, and emotional valence. Cortical attention was operationalized using EEG, collected using a 14-channel headset (Emotiv Systems, San Francisco, CA) with electrodes dispersed over the scalp along the 10–20 system [45]. The electrodes made connection with the scalp surface via felt pads saturated with saline solution. The reference electrodes were located at P3 and P4 over the inferior, posterior parietal lobule [45]. All the other channels were measured in relation to the electrical activity present at these locations, sampled at 128 Hz. Impedances were verified and data collected using Emotiv TestBench Software version 1.5.0.3, which exported it into comma-delimited format for subsequent analysis.

Autonomic arousal was operationalized as skin conductance level measured with 8 millimeter (mm) bipolar AG/AGCL electrodes filled with electrically neutral gel and adhered to the palmar surface of the nondominant hand after lightly hydrating it with distilled water. A Coulbourn Instruments skin conductance coupler delivered 0.5 V (volts) to the palmar surface and conductance was sampled by a Coulbourn A.D./DA (analog to digital/digital to analog) board at 125 Hz using VPM software version 12.8 [15]. Emotional valence was operationalized as the relative activation of the corrugator supercilli muscle group. Corrugator EMG was measured using a pair of mini (4 mm) reusable AG/AGCL electrodes filled with electrolyte gel placed above the subject's left eye after dead skin cells had been removed by a skin preparation pad containing rubbing alcohol and pumice. The bipolar corrugator measures were collected using a Coulbourn bioamplifier with high-pass filters set at 8 Hz. The full wave signal was rectified and then contour integrated online at a time constant of 100 ms prior to sampling.

Controls and Manipulation Checks

It was essential to ensure that the participants perceived the simulator as a real team discussion. All of the participants completed postsession questionnaires that asked if they had noticed anything unusual about the team discussion. A variety of distractor questions (e.g., satisfaction with discussion, perceived effectiveness) were included to better ensure that manipulation check question did not stand out. Ten participants suspected the discussion was not with real people and their data were removed prior to analysis.

Markers were manually inserted by the researchers into the EEG data to indicate the onset and the end of the simulator's text discussion. A timestamp generated by the simulator program was used to identify precisely when each statement was displayed. This timestamp marker for each target statement was then matched to the EEG data. All of the experimental sessions were video-recorded and the timestamps on the recordings were used to verify the time-locking of the data to the target statements.

Procedures

The participants completed the experimental procedure individually after providing informed consent approved by the university's Institutional Review Board. The experiment took place in an individual laboratory at a research institute. The entire research session took less than 90 minutes, and included measures associated with unrelated studies. The experiment was controlled by MediaLab software [51].

The participants were seated in a high-back chair to minimize movement. They used a standard keyboard and mouse. The protocol began with a 10-minute series of personality questionnaires for another study. The experimenter attached the physiological electrodes and fitted the EEG apparatus, answering any questions posed by the participant. After obtaining adequate impedance readings for the EMG and EEG measures, the protocol continued with another brief personality questionnaire unrelated to this study for 10 minutes.

The participants then received information on the college admissions task and the prediscussion information. They were instructed that they would use this information to make their decision and that they would be sharing the information with the team later. The participants were given three minutes to read the information, which was presented in the form of a data table, and decide which three of five students they would choose to admit.

After making their prediscussion decisions, the participants were instructed on the nature of the discussion task. They were told that the other team members were located at various places across campus and not in the research laboratory because physiological data were not being collected from them. The participants were told that the discussion would last for 12 minutes and were reminded that each team member received some unique information. They were instructed to share all the information they knew and read all the information provided by others.

In total, the EEG apparatus was on the participants for about 30 minutes, during which the electrodes remained damp with the saline solution. Impedances values for each cranial location remained acceptable for the duration of the experiment. When the discussion simulation was completed, the experimenter removed all the physiological data collection sensors. The participants then completed the postexperiment questionnaire. Finally, they were debriefed, told of the deception, asked not to inform others of the deception, and thanked for their time.

Data Cleaning and Preparation

EEG data were cleaned and analyzed using EEGLab version 11.0.0.0.b [21]. One limitation of EEG is that cortical bioelectrical activity is extremely small in magnitude when compared to muscle movements across the head. Therefore, participant movement introduces artifacts of high-frequency and magnitude into the EEG data. The most notorious of these is the ocular or “eye motion” artifact. These were removed using two methods: EEGLab probability calculations and visual inspection. The EEGLab artifact rejection algorithm uses deviations in microvolts greater than three standard deviations from the mean to reject specific trials. However, additional artifacts are also apparent to the trained eye, so visual inspection of trials is essential in artifact removal [21]. We had 63 “trials.” Each trial was a target statement in the simulator script that was classified as one of the five types of information statements: factual supporting, factual challenging, normative supporting, normative challenging, and irrelevant. Using published guidelines [20] we rejected approximately 20 percent of the trials based on muscular artifacts.

In addition to trial-by-trial removal of artifacts, occasionally specific EEG channels must be rejected in an individual subject's data due to unacceptable impedance levels. This was done in the current study using an automatic impedance detection feature of EEGLab. Single channels were detected and removed from 18 participants prior to analysis. No subject had more than one channel rejected.

Electrodermal and facial EMG data were aggregated to mean values per second using VPMANLOG 7.2 [16]. Change scores were calculated by subtracting the physiological level at the onset of each target statement during the online discussion from each subsequent second across a six-second window. For several reasons (computer, equipment, or human error during data collection) the final number for physiological analyses was 28.

Independent Components Analysis Decomposition of EEG Data

The first step of the EEG analysis was an independent components analysis (ICA) at the individual level. A common problem in neuroimaging research results from the collection of large amounts of data that, based on the central limit theorem, become normally distributed. However, the brain is comprised of discrete patches of cortex that are very active at some points in time and relatively nonactive at others (i.e., activity is not normally distributed across the scalp) [76]. ICA overcomes this problem by taking this Gaussian data and rotating it until it becomes non-Gaussian, thereby isolating independent components of activation.

Initially, an EEGLab ICA performs a principal components analysis (PCA). At each electrode site the program assesses which of the other electrode sites account for the most variance in the signal. Taking these weighted values it then relaxes the orthogonality constraint of PCA to isolate individual components of activation [76]. Each ICA component then represents a pattern of activation over the entire brain, not solely the activity present at a specific electrode. The number of independent components (ICs) depends on the number of electrodes in the data set, as the algorithm is working in an *N*-dimensional space (where *N* is the number of electrodes). Most of the participants in the current study generated 14 distinct ICs, because our recording device had 14 electrodes. The 18 participants with a single electrode removed from analysis due to poor impedance each produced 13 ICs.

Finally, using the *K*-means component of EEGLab the independent components at the individual level were grouped into clusters containing similar components. This was done using recommended procedures that clustered similar ICs according to their latency, frequency, amplitude, and scalp distribution [20]. Twelve clusters were generated and evaluated for the final analysis.

Results

Cognitive Responses to Information

The *K*-means cluster analysis produced three clusters of interest. These were selected initially according to the number of subjects and ICs represented in each cluster and later supported via visual inspection of scalp maps indicating activity occurring in brain regions of neurophysiological relevance to our hypotheses. Due to the idiosyncratic nature of neural activity within each participant, some did not produce ICs in each cluster. For example, one cluster contained data from 38 participants, meaning that 6 of the 44 participants did not produce neural responses statistically related to the others in the regions identified by the cluster. Differences in brain lateralization or structure are likely explanations for the differences in the number of subjects included in each cluster. Another possibility is the signal-to-noise ratio in the EEG signal, which, as mentioned previously, is much smaller than other types of bioelectrical activity (e.g., muscular or ocular). The clusters were nevertheless determined to be representative of the neural activity in the entire group of experimental participants because the majority produced at least one IC in each of the four selected clusters.

EEG measurement provides a plethora of data that can be decomposed using different analytical procedures. We chose to use event-related spectral perturbation (ERSP) for its ability to model both time and frequency changes occurring in the ICs over the time window specified. The ERSP produces a latency-by-frequency image that shows mean changes in log power from some prespecified baseline mean value [71]. In this experiment we used the 500 ms preceding the target phase onset as our baseline mean. A latency exists between stimulus onset and reaction to the stimulus because the participant has to read the statement. Prior research has established that the average reading rate is five words per second [14]. Our target statements were 5–8 words, so we assumed that most differences would be observed after 1,000 ms. However, the participants were expected to begin making assessments of relevance from the moment they began reading. Therefore, we generated ERSPs from stimulus onset to 4,000 ms after stimulus onset.

We generated ERSPs that included the alpha band frequency (8–13 Hz), which is closely tied to attention and cognitive load [59]. Decreases in log power over the latency window indicate increased attention during that timeframe. EEGLab provides statistical comparisons of ERSPs. We set the statistical threshold at $p < 0.01$ and corrected for multiple comparisons using the false discovery rate. The false discovery rate uses the approach of Benjamini and Hochberg [8] to minimize Type I error with only a marginal loss of statistical power.

The first cluster is geographically dispersed on the outer regions of the scalp, demonstrating high activation in the frontal, temporal, and occipital regions of the brain (which we term the "FTO cluster") (see Figure 1). This cluster contained data from 38 subjects and 144 ICs. While there seems to be some occipital activation, the left temporal and left frontal activation appear to be more pronounced. These areas are highly involved in language processing, containing both Wernicke's area (language recognition) and Broca's area (language production) [82]. The omnibus test showed significant differences across the five types of information from stimulus onset to three seconds. Most of the activation occurred in the lower-to-middle alpha frequency band, but a portion between 1.5 and 2.0 was significant for nearly the entire alpha frequency band. The differences in early latencies likely represent occipital processing of visual stimuli. The latter latency differences suggest that this information was

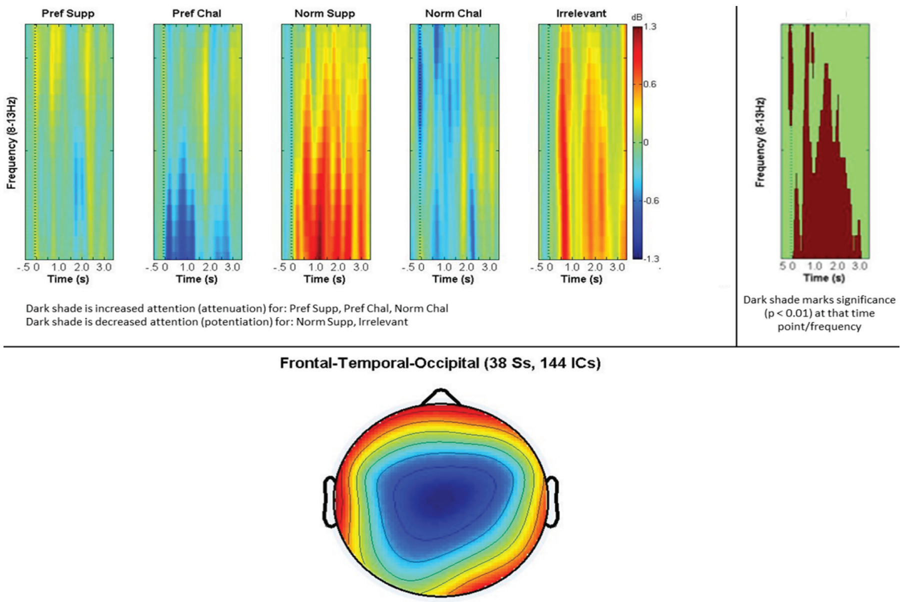

Figure 1. ANOVA of the Different Information Types for the Frontal-Temporal-Occipital (FTO) Cluster

Notes: In the top panel, the far right graph shows areas of significance ($p < 0.01$) adjusted for false discovery rate. The bottom panel is a scalp map showing spatial activation of the FTO cluster. The FTO cluster contains 38 subjects and 144 ICs. Frontal and temporal regions include regions that are vital to working memory, attention, and language processing. The time is along the *x*-axis, including a 500 millisecond prestimulus baseline. The *y*-axis shows the alpha frequency band (8–13 Hz). The omnibus test of significance shows significant differences among the five types of information across the 0–3.0-second time window from 8–13 Hz of the alpha frequency band.

relayed forward to the frontal and temporal regions for further processing, such as the initial consideration of incoming information.

Follow-up pairwise comparisons showed significant differences in processing between preference-supporting and irrelevant information (see Figure 2). The difference was observed from latency 1.5 to 2.0 seconds between 8 and 12 Hz. Comparison of ERSPs shows decreases in log power of alpha frequency in preference-supporting information when compared to irrelevant information, indicating higher processing of information for the preference-supporting information (Panel A). Pairwise comparisons between preference-challenging and irrelevant information show significant differences in the lower alpha frequency band between stimulus onset and three seconds. However, around two seconds there are also significant differences observed in the upper alpha frequency band. This pattern indicates increased processing of preference-challenging information (Panel B). Pairwise comparisons of normative-supporting information showed no significant differences in processing when compared to irrelevant information (Panel C). Finally, significant differences were observed between the processing of

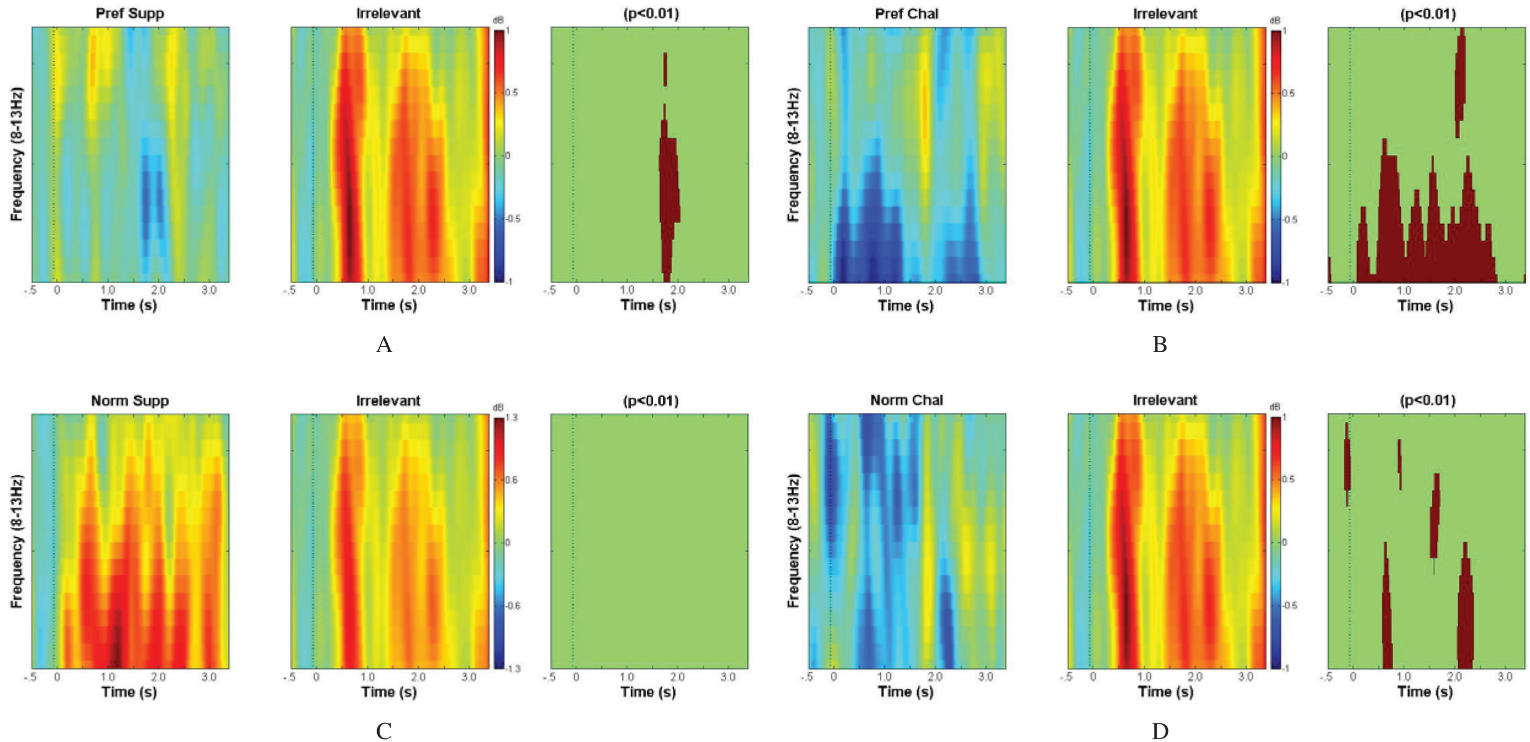

Figure 2. Pairwise Comparisons of Each Information Type Against Irrelevant Information

Notes: The third box in each panel shows areas of significance at $p < 0.01$ adjusted for false discovery rate. Panel A shows significant attenuation of alpha frequency between 1.5 and 2.0 seconds across the entire alpha frequency band. Panel B shows significant attenuation of alpha around 8–11 Hz activity from 0 to 3 seconds, with one area of significance in the upper alpha frequency band at 2 seconds. Furthermore, Panel D shows significant attenuation of alpha in the mid-upper alpha frequency band at 0.8 seconds, 1.5 seconds, and lower alpha frequency at 2.0–2.5 seconds for normative challenging information. No significant differences in alpha power were observed between normative supporting and irrelevant statements (Panel C).

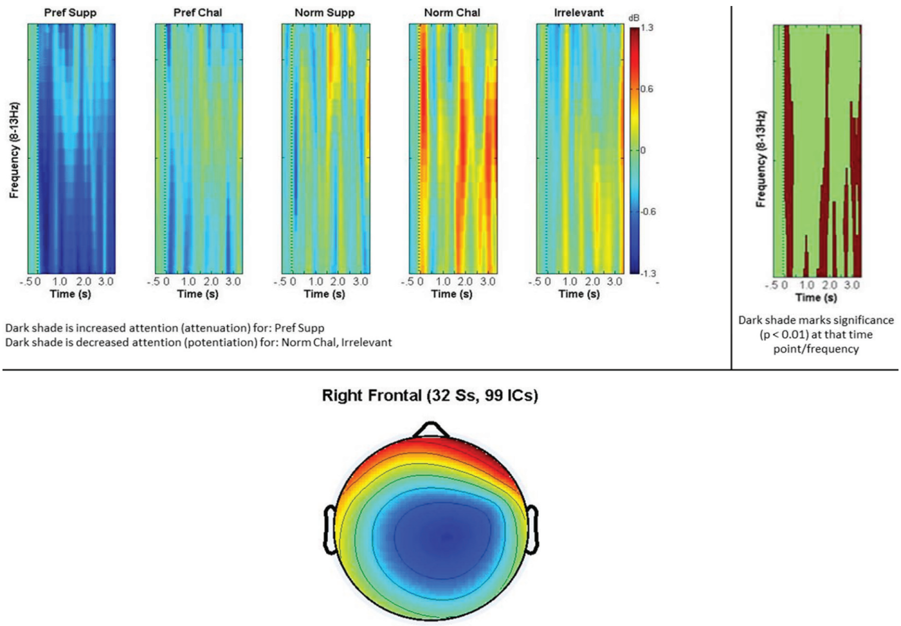

Figure 3. ANOVA of the Different Information Types for Right Frontal (RF) Cluster

Notes: In the top panel, the far right graph shows areas of significance ($p < 0.01$) adjusted for false discovery rate. The bottom panel is a scalp map showing spatial activation of the RF cluster. The RF cluster contains 32 subjects and 99 ICs. The RF region contains areas that are involved in the contextual processing of information. The time is along the *x*-axis, including a 500 millisecond prestimulus baseline. The *y*-axis shows the alpha frequency band (8–13 Hz). The omnibus test of significance shows significant differences among the 5 types of information across the 0–3.0-second time window from 8–12 Hz of the alpha frequency band, with the most pronounced differences occurring between 1.5–2.0 seconds and 2.5–3.0 seconds.

normative-challenging and irrelevant information occurring between 0.5 and 1 seconds in the lower alpha band and from 1.5 to 2.5 seconds in the middle and lower alpha frequency bands. This pattern suggests increased processing of normative-challenging information (Panel D).

The second cluster represented high magnitude activation ICs centered over the right frontal portion of the brain (termed the "RF cluster") (see Figure 3). This cluster contained data from 32 subjects and 99 ICs. While there is some left frontal activation in this cluster, the majority of the activation is located over the right frontal regions of the brain. Research shows activation of the right frontal regions during retrieval of episodic memory [43]. Increased processing in the right frontal lobe has been shown to be related to increased contextual monitoring demands, suggesting a role in determining context of memory in working memory [43]. Increasingly, the right frontal lobe is being recognized for its ability to place information into context with prior episodic and semantic memories [3, 43]. Changes in alpha frequency over the right frontal regions could indicate processing of information against information previously stored in memory [77]. The omnibus test shows significant differences across the five types of information. The significant differences can be seen across the entire alpha frequency band. A significant difference was observed from stimulus onset to 500 ms. Furthermore, another significant difference is observed across the entire band at 1.5–2.0 seconds. Finally, from 2.5 seconds onward, there are significant differences among the types of information in the lower two-thirds of alpha.

We conducted follow-up pairwise comparisons of all the types of relevant information against irrelevant information (see Figure 4). A significant difference was observed in the processing of preference-supporting information against irrelevant information. These differences occurred in the lower-to-middle alpha frequency band. The ERSPs show a decrease in the log power of alpha in the preference-supporting information, indicating increased processing of preference-supporting information as compared to irrelevant (Panel A). Comparisons of processing the other types of information showed no significant differences compared to irrelevant information.

The third cluster represents high magnitude ICs centered over the left frontal portion of the brain (termed the "LF cluster") (see Figure 5). This cluster contained data from 29 subjects and 98 ICs. While there is some right frontal activation in this cluster, the majority appears to be located over the left portion of the frontal lobe. Left frontal activation incorporates DLPFC, which is central to working memory processing, attention, and decision making [5]. Furthermore, emotional processing occurs asymmetrically across frontal brain regions, with left hemisphere activation indicative of positive affect [74] or approach motivation [41]. The omnibus test shows significant differences across the five types of information (Figure 5). The significant differences occur over the entire range of the alpha frequency band, with the most pronounced differences occurring after one second. This finding indicates the information was processed differently across conditions.

We again conducted pairwise comparisons of each type of information against irrelevant information to find which were processed differently than irrelevant information (Figure 6). The pairwise comparisons revealed significant differences between normative-supporting information and irrelevant information across the entire alpha band. Furthermore, the significant differences occurred in lower alpha frequency bands from 0 to 1 second and across the entire frequency band from 1 to 3.5 seconds (Panel C). The difference shows a decrease in the mean log power of the alpha frequency band, which indicates increased attention to normative-supporting information over irrelevant information. Comparisons of normative-challenging information provided small portions of significance at 2 and 3 seconds in the middle of the alpha frequency band (Panel D). Comparisons of preference-supporting and preference-challenging information showed no significant differences in alpha band activity between them and irrelevant information (Panels A and B, respectively).

Therefore, we conclude that H1a, H1b, H2a, and H2b are supported.

Emotional Responses to Information

The psychophysiology change scores from one second before onset of each target statement were submitted to a 5 (type) × 8 (repetition) × 7 (time) repeated measures

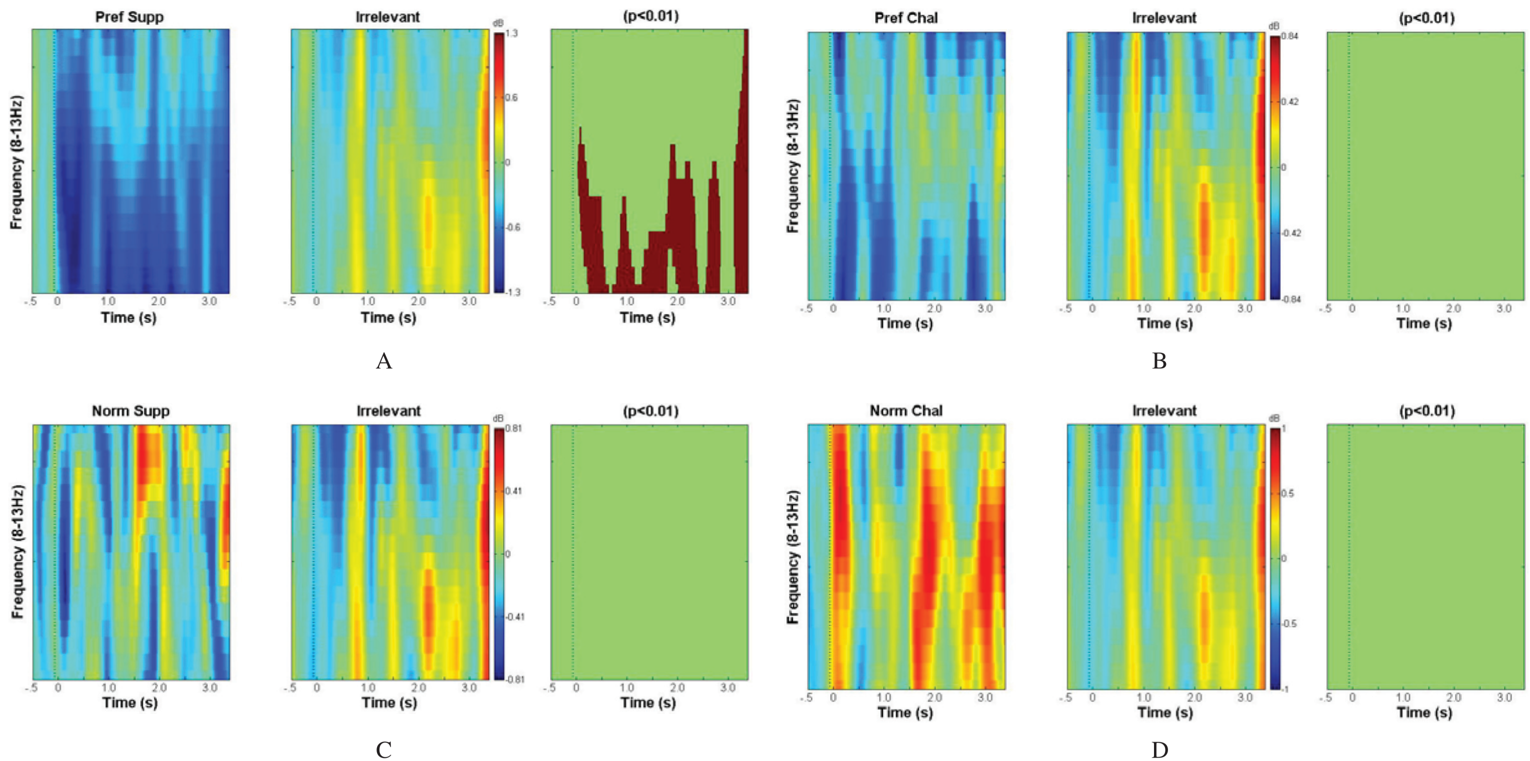

Figure 4. Pairwise Comparisons of Each Information Type Against Irrelevant Information

Notes: The third box in each panel shows areas of significance at $p < 0.01$ adjusted for false discovery rate. Panel A shows significant attenuation of alpha frequency between 0 and 3.0 seconds across the lower alpha frequency band. It also shows activation after 3.0 seconds across the entire alpha frequency band. Panels B, C, and D show no significant difference in processing of preference challenging, normative supporting, or normative challenging when compared to irrelevant.

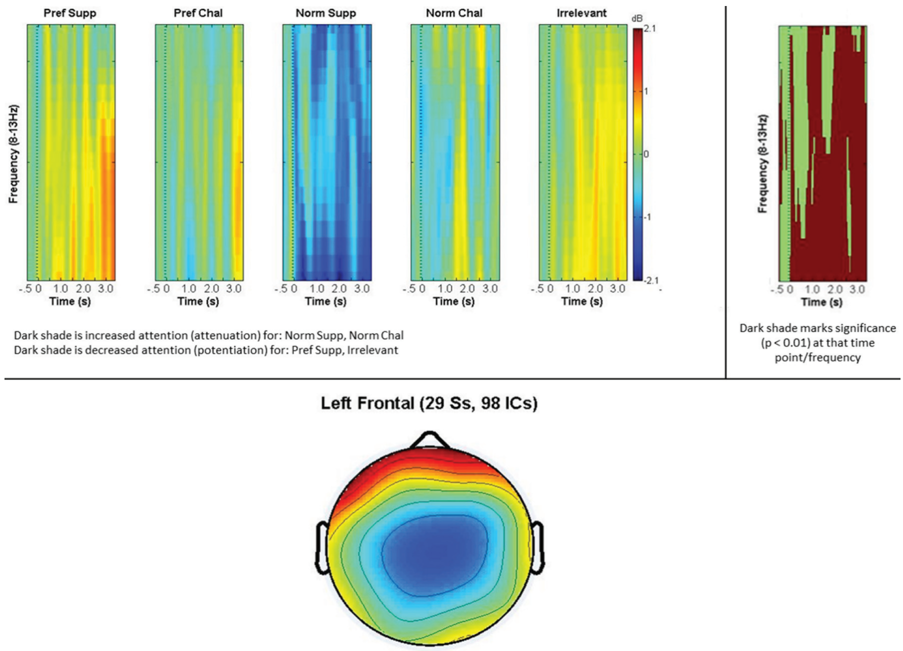

Figure 5. ANOVA of the Different Information Types for the Left Frontal (LF) Cluster

Notes: In the top panel, the far right graph shows areas of significance ($p < 0.01$) adjusted for false discovery rate. The bottom panel is a scalp map showing spatial activation of the left frontal cluster. The left frontal cluster contains 29 subjects and 98 ICs. Left frontal regions include areas vital to working memory and language production. Time is along the x-axis, including a 500 millisecond prestimulus baseline. The y-axis shows the alpha frequency band (8–13 Hz). The omnibus test of significance shows significant differences among the five types of information across the 0–3.0-second time window across the alpha frequency band.

analysis of variance (ANOVA). The results for the corrugator data analyses were not statistically significant, with all meaningful F-values less than 1. This suggests that there were no consistent changes in emotional valence due to the type of information received. H3 was not supported.

The omnibus F-test for the skin conductance data over a six-second window approached significance ($F(4, 108) = 2.364$, $p = 0.11$). The change scores over time can be seen in Figure 7. Recall that we argued that there would be initial arousal in response to incoming information, but only preference-supporting information would receive additional processing and trigger later increases in arousal. Also recall that there is a latency of 1,000–3,000 ms in skin conductance response. Figure 7 shows a general increase in arousal 1–4 seconds after information onset, with the exception of normative-supporting information, which leads to decreased arousal. Arousal in response to preference-challenging and irrelevant information drops between the fifth and sixth second post onset. Paired t-tests for the change scores at six seconds following the onset of the information finds arousal responses to be significantly greater

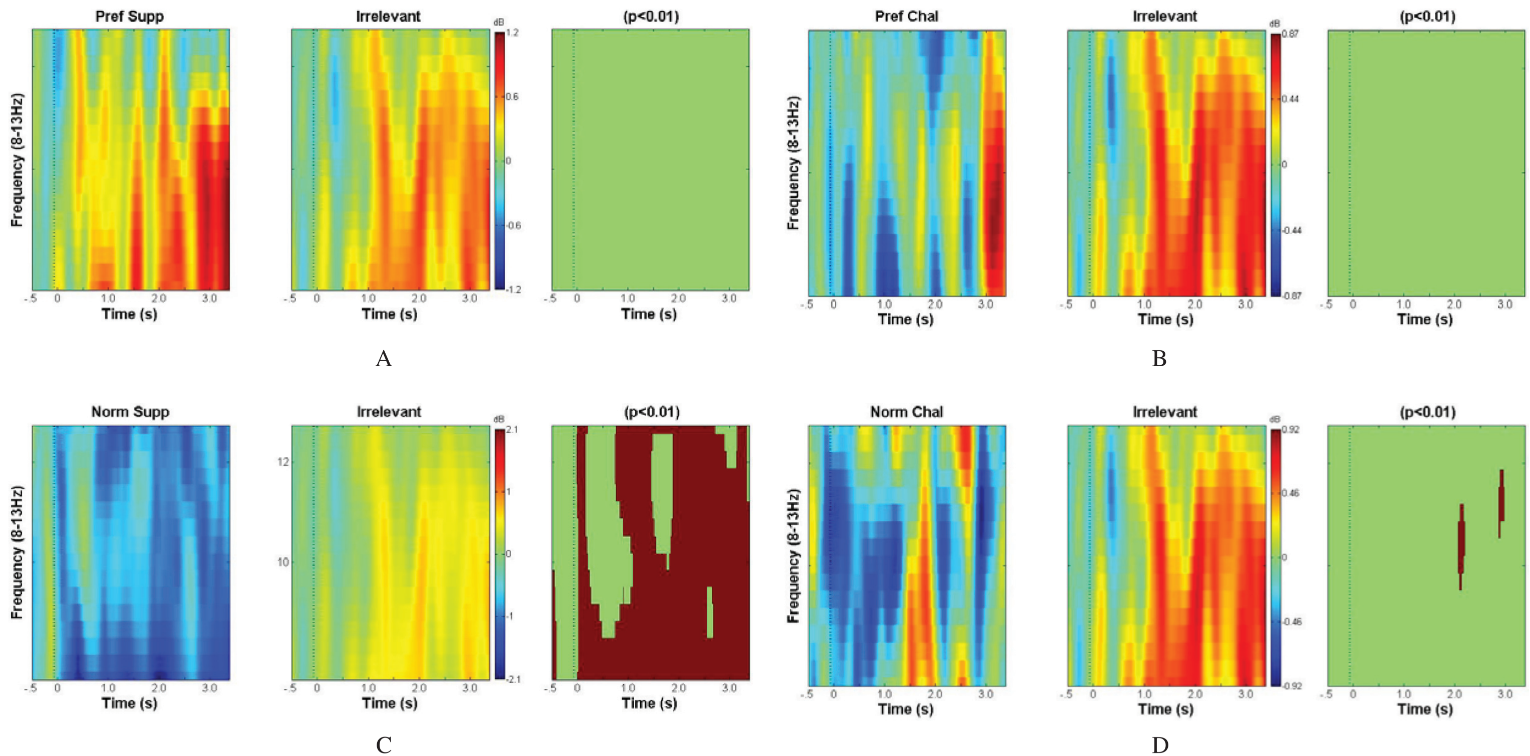

Figure 6. Pairwise Comparisons of Each Information Type Against Irrelevant Information.

Notes: The third box in each panel shows areas of significance at $p < 0.01$ adjusted for false discovery rate. Panel C shows significant attenuation of alpha (8–13 Hz) activity over the DLPFC and Broca's area for normative supporting information. Furthermore, Panel D shows significant attenuation of alpha in the mid-upper alpha frequency band after 2.0 seconds for normative challenging information. No significant differences were observed between preference supporting (Panel A) or preference challenging when compared to irrelevant (Panel B).

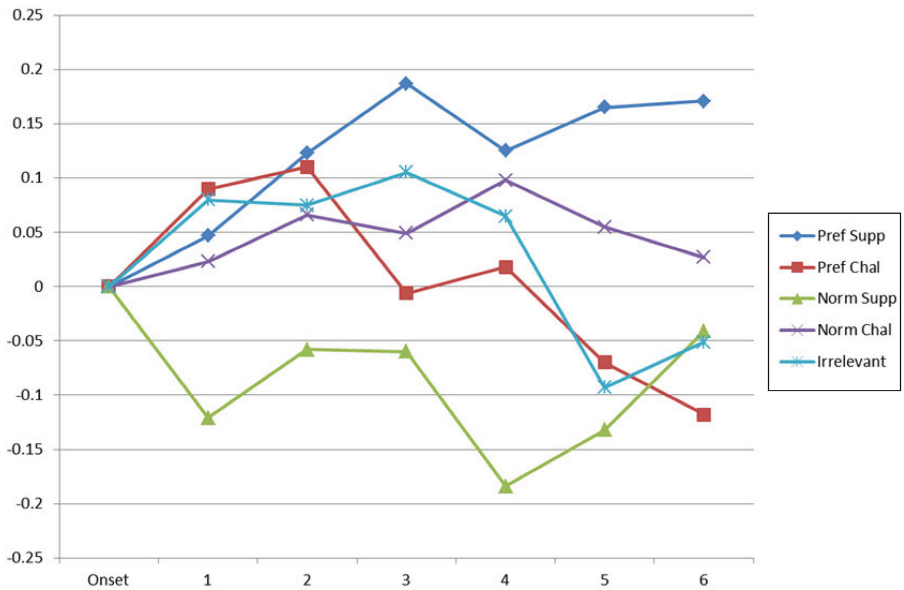

Figure 7. Change Scores in Skin Conductance Following Onset of Target Statements

for preference-supporting information than for both preference-challenging information ($t(27) = 1.75$, $p = 0.045$) and normative-challenging information ($t(27) = 1.89$, $p = 0.035$). We conclude that H4 is supported.

Discussion

A summary of our primary findings is presented in Table 1. Our results show that when participants in a virtual team discussion receive information from other team members, they process that information in different ways depending on the type of information received. This indicates that a primary cause of poor information processing by members of virtual teams is confirmation bias, rather than information overload, because the information is processed, and processed differently depending on its meaning.

When participants receive factual information that supports their prediscussion preferences, they allocate more cognition—compared to irrelevant information—to figuring out what the information means. Furthermore, preference-supporting information results in more cognition (again compared to irrelevant information) later in the dynamic processing stream, with participants likely matching this new information to what they already know. This interpretation of later processing of preference-supporting information is supported by the fact that it also triggers increased emotional arousal evident in the skin conductance data. We interpret these cognitive and emotional patterns as suggesting that participants think about and become activated by preference-supporting factual information.

Table 1. Summary of Results

Type of information	Cognitive effect	Emotional effect
Preference supporting	Limited activation of the FTO cluster, suggesting language processing and initial classification of information Activation of the RF cluster, suggesting increased working memory, comparison of new information to information already known	Increased emotional arousal demonstrated in skin conductance
Preference challenging	Activation of the FTO cluster, suggesting language processing and initial classification of information	
Normative supporting	Activation of the LF cluster, suggesting approach motivation while considering the positive meaning of the information	
Normative challenging	Limited activation of the FTO cluster, suggesting language processing and initial classification of information Very limited activation of the LF cluster, suggesting consideration of the meaning of the information	

In contrast, when participants receive factual information that challenges their prediscussion preferences, they spend more cognition—compared to irrelevant information—figuring out what the information means. Once they do assess meaning, the challenging information is not further considered elsewhere in the frontal cortex. We do not see any further activation in working memory, and we do not see increased activation in contextual processing regions of the brain. These patterns suggest that once participants determine that information challenges their prediscussion preferences, they feel the information is less interesting and do not think about it further.

The process of clarifying preference-challenging information may, in fact, provide an explanation for the lack of statistical significance in the corrugator muscle response data. We hypothesized that the negative affect in response to preference-challenging statements would be sufficient to elicit corrugator activation. Such activation has been found in response to negatively valenced words presented on a computer screen [44]. However, that work used single words that are expected to be more quickly processed than the five to eight word phrases utilized in the current study. The extra time needed to read the entire phrase and determine that it was preference challenging might have obscured any peripheral emotional response. Another possibility is that words used in previous studies (e.g., [91]) are much more strongly valenced (e.g., death, cancer) than those used in our chat simulator script. In hindsight, the expectation that participants would respond strongly when having an unknown team member disagree with their prediscussion decision surrounding a low-salience issue was likely misguided.

Future research should investigate the use of words that are more inflammatory in preference-challenging statements as well as focus decision-making tasks around topics of greater personal relevance to experimental subjects to see if these variables impact peripheral physiological measures of negative affect.

When participants receive normative information that supports their prediscussion preferences, they allocate few cognitive resources figuring out what the information means (presumably because it is obvious). Rather, it seems that this information is fed into working memory and undergoes processing in the left frontal region associated with positive affect and appetitive activation. These patterns suggest that normative-supporting information triggers thoughts of what it means to have other group members support one's opinions, but little else.

When participants receive normative information that challenges their prediscussion choices, they spend more cognition figuring out what the information means, but little other cognition (see Table 1). Interestingly, this information also triggers increased activation in the cortical motor regions, suggesting, perhaps, that participants are thinking about typing a response. These patterns suggest that normative-challenging information triggers thoughts of what it means to have other group members challenge one's opinions, and perhaps induces plans for responding to those challenges. An alternative explanation for this result is the subjects' anticipation, during the team simulation, of each subsequent statement pushing the prior statements up the screen as the chat progressed. However, this explanation is less likely, as we observed differential activation in the alpha band compared to irrelevant information, and anticipation of scrolling would be expected to be equal across the different types of information.

Taken together, these neural patterns suggest that participants in virtual team discussions think more about, and get more emotionally aroused by, factual information that supports their prediscussion choices. Normative information that supports prediscussion choices also receives extra cognitive attention, but in the area of the brain associated with positive cognition, suggesting that individuals savor the thought that others agree with them. However, facts and normative statements that challenge prediscussion preferences receive little attention. To our knowledge, this is the first study to show neurological evidence suggesting cognitive processes underlying the confirmation bias phenomenon. Unfortunately, this is also the ideal prescription for poor decision making in a hidden profile task when team members have different information and it is important to integrate facts from everyone, a common situation in organizations when participants come from different parts of the organization [85].

Our findings suffer from the normal limitations of laboratory research. To increase control, we studied undergraduate students performing an artificial task with a team simulator. One of the inherent limitations of using a simulator is that participants cannot be asked to reach a consensus decision because there are no other team members in actuality. Thus, the decision setting is closer to one in which team members vote, rather than reach a unanimous decision. One issue in laboratory research is external validity and the ability to generalize to other contexts, especially those in organizations. We do not generalize from one context to another, but instead generalize to and from theory [68]. Our study provides empirical evidence that the theory of confirmation bias is at work in this context. When generalizing to another context, the question would be, what elements of the theory would inhibit its applicability to the new context, rather than what are the characteristics of the context in which empirical evidence supporting the theory was gathered? More research is needed to determine if our findings apply to other contexts. Despite these limitations, we believe there are important implications for research and practice.

Implications for Research

Our findings illustrate the importance of considering how an IS affects individual cognition. Our findings suggest that a primary cause of poor decision making in virtual teams is confirmation bias, rather than information overload. While the immediate implications include designing collaboration systems that mitigate an individual's confirmation bias, the more important contribution to the IS literature lies in shifting our focus to designing collaboration systems that mitigate the limitations of individual cognition, rather than continuing to focus exclusively on issues of group information exchange. This study showed that an individual team member's cognitive bias affected information processing during a virtual team discussion. Leveraging the findings of individual cognitive studies can lead to new designs for the information technology artifact. Hevner et al. [46] provide design science guidelines that include addressing problems that are relevant to the field (e.g., poor decision making in virtual teams), evaluating effective design artifacts to address these problems (e.g., a new system to alleviate cognitive biases), and providing contributions to design methodologies. We believe this paper addresses a relevant design science problem (guideline 2 in [46]) and contributes by opening a new door for utilizing design methodologies (guideline 4 in [46]).

One specific avenue for future research from our study includes examining ways to design collaboration systems to alleviate confirmation bias, now that we know it is a primary concern in small virtual teams. Thus, we encourage future research to focus on identifying the sources of and mitigation techniques for confirmation bias. We used small virtual teams, which are common in today's organizations [1], so we are unable to assess whether confirmation bias is the principal factor for poor decisions in larger virtual teams. It is possible that information overload may still be a factor in some virtual team work (e.g., in cases with large teams). However, we believe that a focus on confirmation bias will lead to more fruitful inquiry.

Confirmation bias is inherently an *individual* process, not a *team* process. Much past virtual team research has focused on a social psychology–based framework of process gains and process losses that collaboration technology can introduce into the virtual teamwork process [75]. Such social psychological factors remain important, but we need to place a greater emphasis on cognitive psychology and the ways in which individual cognition influences virtual teamwork [42, 60]. Media synchronicity theory, for example, deliberately expands the focus of virtual team interactions to include both social psychology–based factors of communication and cognitive psychology–based factors of individual information processing [26]. We need more research on individual cognition and individual decision biases in the context of virtual team decision making to better understand how the design of the virtual environment can affect—for better or worse—individual cognition in virtual teams.

For example, it may be possible to design procedures into teamwork to mitigate confirmation bias. Directing team members to consider new information is not likely to work. We informed the participants in our study that each of them had received incomplete information and that they would need to share their information and think about the information they received from other team members in order to make a good decision. Nonetheless, they still ignored information challenging their prediscussion preferences. Kray and Galinsky [62] show that a putative team-building exercise can be used to induce counterfactual information search and processing—the search for and use of information that challenges a team member's initial prediscussion preferences. By introducing such counterfactual priming procedures it may be possible to mitigate some of the confirmation bias we observed.

The question for IS researchers is how we can better design collaboration technology to reduce confirmation bias. Confirmation bias may be a deliberate action, where a team member explicitly considers information that challenges his or her beliefs and chooses to discount it, or it may be subconscious, where a team member simply overlooks disconfirming information because he or she is not sure of its relevance because it does not fit his or her current mental model of the decision. If the bias is subconscious, then inducing team members to explicitly consider all new information may reduce the bias. For example, the technology could encourage them to deliberately sort the incoming information into important and unimportant folders [47]. Alternatively, organizing information and explicitly labeling it as supporting or challenging each alternative might help reduce a subconscious tendency to ignore it—and make it more difficult to deliberately hide unwanted information.

Another important set of implications for future research is indicated by the lack of statistical significance in the corrugator EMG data. The challenging statements provided by team members were thought to evoke cognitive dissonance in participants, a situation conceptualized as negative in valence, whereas this was not seen in the frown muscle activation, even early on in the time course of processing when initial valance categorization of supportive versus challenging statements was expected to be observed. In the clarity of hindsight, however, this is may not be altogether surprising, given the low emotional impact of the decision-making task at hand. Future research should increase the salience of the decision-making outcome in some manner, for example, by attaching a monetary reward for the research subject if the team reaches the correct decision.

A final consideration for future research arises from our use of NeuroIS methods. We used EEG, EDR, and facial EMG to open the black box of virtual team member decision making and provide further insights into cognition and emotion than studies using more traditional behavioral and observational measures. The EEG data showed that different information triggered different patterns of cognition, while the EDR data showed that different information triggered different emotional responses. Neither of these findings could have come from traditional behavioral research. Thus, we believe that this study adds to the growing body of work showing that the use of these methods has the potential to add new insights into IS research (e.g., [30]). The novel application of these techniques to IS theories can provide deep insights into previously elusive paradoxes or conundrums.

Implications for Practice

One important implication for practice is the need for virtual teams to overcome confirmation bias to make better decisions. Strengthening instructions for team members who engage in virtual team decision-making tasks to consider and carefully evaluate ideas that are counter to their initial preference may enhance processing of the information that challenges their initial preferences. Because preference-supporting information is routinely considered in the context of virtual team decision-making tasks, team members should pay extra attention to preference-challenging information and deliberately seek to understand what it means and how it affects their current understanding of the decision alternatives.

We believe that virtual team leaders should encourage and model this active pursuit of preference-challenging factual information. Leaders routinely intercede to direct and redirect team behavior, although the triggers for this action are typically more obvious than the often subtle discounting of preference-challenging information [88]. Encouraging team members to label their factual contributions as supporting or challenging specific alternatives may mitigate confirmation bias. Likewise, routinely summarizing known facts and organizing them as supporting or challenging specific alternatives may avoid overlooking preference-challenging information.

Conclusion

We conclude that a primary cause of poor virtual team decision making is due to confirmation bias: team members focus their cognitive resources on factual and normative information that supports their prediscussion preferences, rather than deeply considering information that challenges them. Furthermore, we provide NeuroIS data to illustrate the processes underlying this well-known bias in decision-making tasks. We need to develop new work processes and new technology features for virtual teams that address this bias by encouraging team members to more fully consider potentially unpleasant information that challenges their preferences. Many of these new processes and features are likely to be based on cognitive psychology theories of individual cognition, rather than on social psychology–based theories of team interaction. NeuroIS will play a vital role in elucidating previously immeasurable relationships that could further our understanding of individual cognitive processes in IS.

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