

Neural Evidence for the Influence of Communication on Cognitive Processing as
Proposed by Quantum Cognition Theory

Dissertation

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By

Lorraine Borghetti

Graduate Program in Communication

The Ohio State University

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Dissertation Committee

Zheng Joyce Wang, Advisor

Jason Coronel

Richard Huskey

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Abstract

The aim of the present study was to examine neural correlates and mechanisms underlying the psychological mechanisms formalized in a computational model of quantum cognition, the belief-action-entanglement (BAE) model. An analysis of frequency band activity in the brain was carried out to test these mechanisms. The BAE model proposes that communication acts as a measurement that interferes with the evaluative processes prior to a decision (Busemeyer, Wang, & Lambert-Mogiliansky, 2009; Pothos & Busemeyer, 2009; Z. Wang & Busemeyer, 2016). Two key mechanisms were conceptualized and formalized in the BAE model: (1) the superposition state which arises from uncertainty and dissonance when deciding between two or more actions, and (2) the transition from a superposition state to a determinate one during the action evaluation process. These mechanisms correspond with the psychological function and timing of two frequency bands. The frontal-midline (FM) theta (3-8 Hz) indexes conflict processing, a state analogous to cognitive dissonance. Parietal alpha power indexes search and integration processes in memory which captures evolution from the superposition state to a determinate one. To test the extent communication influenced these underlying mechanisms, we employed a category-decision paradigm used in behavioral studies of the BAE model. The study manipulated communication in three ways: receiving information, self-expressing, and no communication. EEG data was

collected from 32 participants. The subsequent analysis of FM theta and parietal alpha-beta frequency band activity provided modest support for the effect of communication on the proposed BAE model mechanisms. Specifically, FM theta activity offered initial evidence that communication resolves dissonance or uncertainty in the superposition state. Further, parietal alpha-beta suppression provided support for the proposition that communication modulates the evolution of the cognitive system until a decision is made. Unexpectedly, we found that self-expressing information resolved no more dissonance in comparison to the absence of communication, providing new insights into effects on the sender during communication.

Dedication

I dedicate my dissertation to my husband, Brett Borghetti, and my son, Rolf Woolen.

Their skepticism, insights, humor, love, and support (technical and otherwise) made this journey exponentially satisfying.

Acknowledgments

I would like to thank my advisor, Zheng Joyce Wang, for the many years of dedicated guidance and support during my graduate school journey. From Joyce, I learned to remain open-minded about the unexpected and the unfamiliar while also retaining a healthy skepticism for the desired, e.g., “don’t forget to ask yourself what else these lovely results might mean?” Joyce also imparted to me her enthusiasm for a radically different conception of the human mind, via quantum cognition theory, which I will carry forward into my research after graduation.

I would also like to thank my committee members, Dr. Jason Coronel and Dr. Richard Huskey, for their patience with my many explorations into matching constructs of the mind to activity in the brain. Indeed, it was their emphasis on *mechanisms* that inspired the specific focus of my dissertation. Further, I appreciate the many hours of discussions we shared on related topics – all of which contributed to my growth as a writer and as a scientist.

I would additionally like to thank my colorful cohort for their friendship, comradery, and TLC as we travelled together down the bumpy road that is graduate school, and my lab mates in Joyce’s Communication and Psychophysiology Lab (CAPLAB) who made the long and nerdy discussions over coding etc. feel entirely normal.

Finally, I would to acknowledge the influence of Michael X. Cohen, a neuroscientist and professor at Radboud University in the Netherlands. Though we have never met in person, I've only become proficient in EEG analysis because of Mike's innumerable (and excellent) online courses and tutorials, books, articles, Google discussion group, and online code.

Vita

Education

Doctor of Philosophy in Communication with a Specialization in Cognitive and Brain Science, Ohio State University, August 2019 (expected)

Masters of Arts in Communication, University of Dayton, December 2014

Bachelor of Arts in Political Science, University of Puget Sound, December 1988

Professional Employment Highlights

August 2014 – May 2018: Graduate Associate, School of Communication, Ohio State University, Columbus OH

June 2012 – July 2014: Senior Communication Strategist, Joint Public Affairs Support Element, Norfolk VA

June 2011 – June 2012: Strategic Communication Planner, US Central Command, Tampa, FL

January 2011 – June 2011: Rule of Law Planner, Combined Joint Interagency Task Force 435, Kabul Afghanistan

March 2008 – March 2009: Commander, 128th Mobile Public Affairs Detachment, Baghdad Iraq

October 2005 – March 2008: Senior Public Affairs Officer, Uinta-Wasatch-Cache National Forest, Salt Lake City UT

September 2002 to September 2005: Public Affairs Officer, Utah Army National Guard, Draper UT

Publications

DeAndrea, H., Rhodes, N., Davidson, E., Ralston, **Borghetti, L.**, and Morr, L. (2017).

The state of the field of social norms research. *International Journal of Communication*, 11, 22. Retrieved from

<https://ijoc.org/index.php/ijoc/article/view/6055>

Lee-Won, R. J., Lee, J. Y., Song, H., & **Borghetti, L.** (2017). “To the Bottle I Go . . . to Drain My Strain”: Effects of microblogged racist messages on target group members' alcohol consumption and the role of anger and shame. *Communication Research*, 44(3), 388–415. <https://doi.org/10.1177/0093650215607595>

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Chapter 1. Introduction

Communication is a hallmark of cooperative species and plays a prominent role in human decision-making. In the present work, communication is defined as the transmission of relevant information to a receiver *or* from the sender to the self (Z. Wang & Busemeyer, 2016). The relationship between communication and decision-making has been successfully modelled by computational models of quantum cognition (QC), which draw upon the principles and mathematical formalism of quantum mechanics (Bruza, Wang, & Busemeyer, 2015; Busemeyer & Bruza, 2012). Critically, QC theory and quantum mechanics view systems as fundamentally indeterminate, until measured (Bruza et al., 2015; Busemeyer & Bruza, 2012). According to QC theory, how communication disturbs a cognitive system can be modeled in a way that is similar to how a measurement interferes with entangled particles in a quantum system – a phenomenon known as an interference effect. More relevant to cognitive processing, introducing or communicating information – e.g., the measurement – into an evaluation changes the interpretation of decision variables, in part, by reducing uncertainty (Busemeyer & Wang, 2018b; Z. Wang & Busemeyer, 2016).

QC theory predictions about communication-related interference effects have been supported across a range of experimental paradigms including “irrational” decisions like those in Prisoner’s Dilemma (Pothos & Busemeyer, 2009), motion discrimination

and confidence (Kvam, Pleskac, Yu, & Busemeyer, 2015), measurement effects in advertisements (White, Pothos, & Busemeyer, 2014); sequential effects in belief and attitude updating (Trueblood & Busemeyer, 2011; Z. Wang, Solloway, Shiffrin, & Busemeyer, 2014), interference effects of categorization on decision making (Busemeyer et al., 2009; Z. Wang & Busemeyer, 2016), and data fusion (Busemeyer & Wang, 2018b, 2018a). These studies rely on well-designed behavioral experiments and often sophisticated computational cognitive modeling to test the application of quantum principles to model psychological processes. However, the underlying neural mechanisms assumed by QC models have not been empirically investigated.

Investigating neural mechanisms helps test the psychological mechanisms conceptualized and formalized by computational models of cognition, including QC models. Thus, the main goal of the present study was to provide neural evidence that is consistent with the psychological mechanisms formalized in the QC theory.

Neural data provide real time information about cognitive states that has yielded evidence for underlying mechanisms assumed by numerous psychological theories such as persuasion (Falk & Scholz, 2018) and threat perception (Correll, Urland, & Ito, 2006), and by computational models like the exemplar model of category representation (Mack, Preston, & Love, 2013). Further, neural data affords a rich store of information for evaluating cognitive processes that cannot be detected by behavioral measures alone (Carretié, 2014; De Hollander, Forstmann, & Brown, 2016; Love, 2016; Palmeri, Love, & Turner, 2017; Turner, Forstmann, Love, Palmeri, & Van Maanen, 2017). Because of

its temporal precision, we expected frequency band activity in the brain collected by electroencephalography (EEG) to provide insights about the time-sensitive mechanisms assumed by QC theory. Our hypotheses for frequency band activity were specifically guided by predictions and empirical evidence for the belief-action-entanglement model, a QC model of communication-related effects on decision-making under uncertainty (Busemeyer et al., 2009; Pothos & Busemeyer, 2009; Z. Wang & Busemeyer, 2016).

Mechanisms of the Belief-Action Entanglement (BAE) Model

Wang & Busemeyer (2016) recently developed a category-decision paradigm to test BAE model predictions about communication-as-a-measurement based on an earlier study (Townsend, Silva, Spencer-Smith, & Wenger, 2000). Knowing a category is important for the decision (Smith et al., 2014; Townsend et al., 2000). For example, doctors need to categorize a medical condition before selecting a treatment. Soldiers must categorize an unfamiliar situation as a threat or not prior to deciding upon a course of action. Notably, a category, e.g., a medical condition, and an action, e.g., the treatment, represent an entangled state in quantum cognition (Aerts, Gabora, & Sozzo, 2013). For example, treatment selection *depends* upon the medical condition, and vice versa; when entangled, they create a composite meaning that does not exist when considered separately (Busemeyer & Bruza, 2012). Wang & Busemeyer's (2016) study linked both categorization and decision processes together in a formal computational model where the critical manipulation varied communication about a category prior to a decision task.

Two key underlying processes during the categorization-decision process have been formalized in the BAE model. First, without knowing the category, people are often in a superposition state with respect to deciding between two or more actions. At each point in time, the cognitive system remains undecided across both categories and actions (Busemeyer et al., 2009; Z. Wang & Busemeyer, 2016). In other words, all possible category and action combinations have the potential to be selected, hence, creating an entangled system. Metaphorically, they exist together in synchrony (Busemeyer & Bruza, 2012). Psychologically, such uncertainty results in a superposed state characterized by ambiguous or conflicted feelings (Bruza et al., 2015; Busemeyer & Bruza, 2012; Z. Wang & Busemeyer, 2016). This internal conflict is similar to experiencing cognitive dissonance, an aversive state where behaviors (decisions about actions) and beliefs (about a category) are not aligned (Festinger, 1957). We address cognitive dissonance theory more thoroughly in later sections. For now, it is important to understand the relationship between communication and dissonance. Specifically, communication about the category resolves a superposition state and reduces cognitive dissonance prior to the decision (Bruza et al., 2015; Busemeyer et al., 2009; Z. Wang & Busemeyer, 2016). That is, being informed of a category reduces uncertainty about which action to take; dissonance resolves accordingly. From the BAE model perspective, communication's role in decreasing uncertainty during cognitive processing reflects the "wave function collapse," the crucial effect of a measurement on the quantum system (Z. Wang &

Busemeyer, 2016). In the absence of communication, the cognitive system remains superposed about *both* the category and the action since neither is known or certain.

The second underlying mechanism manifests during the evaluation process after a categorization and flows through the decision about an action. During this time, the cognitive system transitions from an uncertain superposition state over the entangled system to a determinate one (Z. Wang & Busemeyer, 2016). Beliefs about categories and actions exist in parallel to evolve and influence one another; however, decision-makers cannot say precisely what state they are in (Busemeyer et al., 2009). This fuzzy, superposed state exists until the decision point. Once an action is selected, beliefs about the category and decision are updated psychologically to become certain and fully known to the decision-maker. When earlier communication exposes the category, only possible actions are evaluated during the transition. On the other hand, without prior communication, both the category and the action remain under evaluation as the cognitive state evolves.

Across a series of experiments testing the BAE model, Wang & Busemeyer (2016) varied communication in three ways. In two conditions, communication made the category *explicit*. In the first condition, participants were informed about the stimuli's category prior to taking an action. In the second condition, participants self-expressed their beliefs about the stimuli category. The BAE model assumes explicit communication reduces dissonance in the superposition state; however, self-expressing conveys less certainty than receiving category information because the decision-maker

cannot be sure about the veracity of a self-reported categorization. Hence, an earlier self-expressed belief may change during the evaluation of an action prior to the decision. In a third condition, no information was provided about stimuli category, and participants were assumed to categorize the stimuli *implicitly*. Implicit categorization conveys even less certainty about the true state of the category than self-expressing (Townsend et al., 2000). Moreover, the entangling of beliefs and actions may occur after self-expressing and in the absence of communication because of uncertainty about the category; by contrast, entanglement was not expected to occur after receiving information because the category was known (Wang & Busemeyer, 2016). The metaphorical symphony for all potential responses collapses. Accordingly, the BAE model predicted a tiered effect of communication where, in comparison to no communication which resolved the least uncertainty, receiving information decreased uncertainty more than self-expressing.

Wang and Busemeyer (2016) measured the effect of communication on decision-making using response probabilities, e.g., the proportion of possible actions participants selected. Extreme response probabilities suggested an increase in certainty and a corresponding reduction in dissonance during the evaluation process. Though probabilities for experimental variables were systematically varied, findings across the three experiments consistently supported the BAE model's assumption that communication acts as a measurement to resolve uncertainty about a decision.

The BAE model further used utilities to formalize the influence of communication of categorization information on a decision to act (Wang & Busemeyer, 2016). Utilities

represent a set of stable preferences and beliefs that guide decision making (Hastie & Dawes, 2010). Positive utilities were assigned to actions congruent with the category and negative utilities were assigned to actions incongruent with the category, e.g., categorizing a stimuli as “good” then deciding to take a “bad” action against it (Wang & Busemeyer, 2016). Taken from the cognitive dissonance perspective, the assignment of negative utilities to incongruent actions suggest these decisions will elicit more dissonance than decisions assigned positive utilities.

Moreover, utilities for actions interacted with the stimuli as well as the category but only when self-expressing, and this interaction varied by the valence – positive or negative – of the stimuli. In the empirical studies, the stimuli represented either positive or negative *social* associations which remained entangled with actions across the categorization and decision process. The BAE model predicted that self-expressing a category will not produce an interference effect (or reduce dissonance) for a decision to act incongruent with positive social stimuli (Busemeyer et al., 2009; Z. Wang & Busemeyer, 2016). By contrast, an interference effect was predicted and observed for the same condition after receiving information about a category. The empirical evidence was consistent with model predictions. This suggests that self-expressing resolves less dissonance when social values about positive beliefs may be violated.

Neural Correlates of the BAE Model

The underlying mechanisms of the BAE model correspond with the psychological function and timing of two frequency bands: the frontal-midline (FM) theta (3-8 Hz) and

parietal alpha (9-15 Hz; Cohen, 2014b; Klimesch, 1999, 2012). FM theta power indexes conflict processing (Cavanagh & Frank, 2014; Cohen, 2014b; Cohen & Van Gaal, 2013). Defined as a disturbed state when deciding between two or more competing alternatives (Cohen, 2014b), conflict processing is conceptually similar to the cognitive dissonance experienced in a superposition state (Inzlicht, Bartholow, & Hirsh, 2015; Kitayama & Tompson, 2015). Parietal alpha power indexes search and integration processes in memory (Klimesch, 1999, 2012; Lam, Schoffelen, Uddén, Hultén, & Hagoort, 2016; Vassileiou, Meyer, Beese, & Friederici, 2018) which capture the evaluative processes engaged when transitioning from a superposition state to a determinate one. Decreases in parietal alpha power relative to baseline (non-event) neural activity are referred to as “alpha suppression” (Klimesch, 2012). Frequency band activity is believed to represent neural oscillations which facilitate communication between structures in the brain. Though structural involvement cannot be inferred directly from electrode location, evidence from source estimation, EEG-informed fMRI, and invasive recordings link neural activity in frontal cortical structures, especially the medial prefrontal cortex (mPFC) and anterior cingulate cortex (ACC), with increases in FM theta power and in parietal cortical systems with suppressed alpha power (Cavanagh & Frank, 2014; Cohen, 2014b; Foxe & Snyder, 2011; Gratton, 2018; Gratton, Cooper, Fabiani, Carter, & Karayanidis, 2018; Mazaheri, Slagter, Thut, & Foxe, 2018).

FM theta band. A large body of work implicates FM theta power in top-down, controlled operations which monitor, identify, and recruit resources to resolve conflict

(Cavanagh & Frank, 2014; Cohen, 2014b; Cohen & Cavanagh, 2011; Cohen & Donner, 2013; Jiang, Bailey, & Xiao, 2018; Mölle, Marshall, Fehm, & Born, 2002; van Driel, Swart, Egner, Ridderinkhof, & Cohen, 2015). Conflict-oriented FM theta activates approximately 200-400 ms after stimulus onset in the frontal-midline electrodes on the scalp. The magnitude of power indicates the degree of control implemented e.g., lower FM theta power values indicate less resource allocation to conflict processing.

In conflict processing experiments, participants are often exposed to pre-target cues assigned different probabilities or assigned as neutral; the cues provide information for subsequent decisions trials (Cooper, Darriba, Karayanidis, & Barceló, 2016; Gratton et al., 2018). While cue operationalization varies widely – from explicit symbols to varied fixation positions to temporally distinct audio tones – the uncertainty they represent serve as a key modulation of conflict processing. For example, van Driel et al. (2015) assigned temporal cues to be probabilistic (80% valid) or deterministic (100% valid) in an adaptation of the Simon Task, a common conflict resolution paradigm. In comparison to deterministic cues, responses preceded by probabilistic cues resulted in greater FM theta activation, indicating that exposure to certain information reduced conflict processing. Similar to communication, cues behave like a measurement which interferes with and reduces conflict during cognitive processing; hence, we expected a similar sensitivity to communication's role in conveying varying levels of certainty. Thus for our first hypothesis, we expected explicit communication about a stimuli category to reduce FM theta activity – reflecting cognitive dissonance – during evaluative processing prior

to a decision in comparison to the absence of communication. In addition, since lower probability cues convey less certainty about a category, we expected self-expressing to result in more FM theta activity in comparison to received communication about a category.

Utilities feature prominently in the evaluation of actions, according to the BAE model (Wang & Busemeyer, 2016). Few studies have investigated the effect of utilities on FM theta activation directly so we draw upon empirical research into incongruent cognitions in the brain. Negative utilities, as defined by the BAE model, engage processes conceptually comparable to incongruent trials or decisions in the cognitive control literature; similarly, positive utilities engage processes consistent with congruent trials (Cavanagh & Frank, 2014; Gratton et al., 2018). Further, incongruent trials evoke more FM theta activation than congruent trials, in part, because prepotent responses must be suppressed. For example, in a study evaluating the effect of implicit primes on conflict processing, FM theta power increased on incongruent trials where participants were exposed to happy faces primed earlier by sad faces; by comparison, congruent trials – where participants were primed by happy faces before exposure to happy faces – resulted in less FM theta power (Jiang et al., 2018). However, FM theta may be present in congruent trials simply because the co-activation of congruent and congruent alternatives creates conflict (Cavanagh & Frank, 2014; Inzlicht et al., 2015). Findings for incongruent/congruent trials guided our second hypothesis: while we expected conflict on all trials, we expected choosing an action with negative utilities to result in more FM

theta activity than deciding upon an action with positive utilities, irrespective of communication condition. Since the available evidence does not suggest that communication (or cues) and utilities interact, we expected communication to result in the same pattern of effects as described in our first hypothesis; an interaction effect was not predicted.

The effect of negative utilities/incongruence on conflict processing may be enhanced for positively valenced social stimuli. Previous work revealed that the brain's value system favors maintaining social connections such that exposure to positive social stimuli increased activity in the relevant neural structures (Falk & Scholz, 2018; Mason, Dyer, & Norton, 2009; Nook & Zaki, 2015). In studies evaluating reward processing, neural activity increased after participants violated norms for fair treatment (Gabay, Radua, Kempton, & Mehta, 2014; G. Wang, Li, Li, Wei, & Li, 2016). These findings suggest that choosing an incongruent action for categories with positive social associations may elicit more dissonance than choosing an incongruent action for categories with negative associations. With respect to communication, this may only occur during self-expressing, which conveys less certainty about the true category allowing for more indecision. Specifically, we expected self-expressing to result more FM theta activity for decisions with negative utilities for categories with a positive social value in comparison to categories with a negative social value. Our hypothesis is consistent with a key prediction from the BAE model for making an incongruent decision

for positive stimuli after self-expressing (Busemeyer et al., 2009; Z. Wang & Busemeyer, 2016).

Parietal alpha band. Parietal alpha power suppression, which emerges between 300-700 ms after stimulus onset in posterior electrodes, represents the “release” of attention and increased allocation of resources to memory operations (Clarke, Roberts, & Ranganath, 2018; Klimesch, 1999, 2012; Lam et al., 2016; Vassileiou et al., 2018). Attentional release can be interpreted as access to and searches through representations stored in memory as necessary to resolve a conflict (Klimesch, 2012). Selected representations are integrated in working memory to produce an updated representation (Clarke et al., 2018; Klimesch, 1999, 2012; Mölle et al., 2002; Vassileiou et al., 2018). These search, integration and update operations indexed by parietal alpha activity reflect a process consistent with the transition from a superposition state to a more determinate one assumed by the BAE model (Z. Wang & Busemeyer, 2016). Entanglement also emerges as an attribute of alpha suppression since activation occurs during the evaluation of meaningfully-related stimuli (Klimesch, 1999; Lam et al., 2016; Meltzer, Fonzo, & Constable, 2009). For example, in a rock-paper-scissors type experiment, evaluating conceptually related pairs, e.g., paper-beats-rock, led to more alpha suppression in comparison to pairs without a predefined relationship, e.g., simply paper and a rock (Meltzer et al., 2009). Using these insights as our guide, we expected the absence of communication to result in more alpha suppression than being exposed to communication as such increases represent search and integration operations over both categories and

actions, which remain entangled until the decision. For the same reason, since it conveys less certainty about a category, we expected self-expressing to exhibit increased alpha suppression in comparison to receiving information. We expected receiving information to result in the least alpha suppression because the cognitive system was no longer entangled, and only potential actions were evaluated (Wang & Busemeyer, 2016).

While the present study used frequency band activity to investigate the underlying mechanisms of a communication-related model of quantum cognition, QC research does not argue that the brain operates on the principles of quantum mechanics. However, some work is being conducted in this area by a different group of scholars (Khrennikov, Basieva, Pothos, & Yamato, 2018). Rather, QC theory applies the formalism of quantum probability to cognitive processes. To increase accessibility for non-technical readers, our discussion remained at the conceptual level. For those wishing for more in-depth discussion of QC theory and the BAE model, details can be found in Busemeyer & Bruza (2012), Wang & Busemeyer (2016), and Busemeyer & Wang (2018a).

Chapter 2. Materials and Method

Participants

Undergraduate students were recruited from a large Midwestern university for course credit and a monetary incentive ($N = 32$, 60.5% female; age, $M=19.78$, $SD = 1.43$). Participants completed the experiment individually in a psychophysiological research lab.

Experimental Design and Procedures

To test our hypotheses, we employed the same category-decision paradigm used in behavioral studies of the BAE model (Busemeyer et al., 2009; Pothos & Busemeyer, 2009; Z. Wang & Busemeyer, 2016). The study design consisted of a 3 (communication: receiving, expressing, none) x 2 (face association: friendly, aggressive) within-subjects factorial design. During each trial, participants were exposed to a face. Based on the cover story, they then categorized the face as belonging to a friendly “good” type guy or aggressive “bad” type guy. Afterwards, they decided to “attack” or “be friendly” based upon the face category. Participants completed two blocks of 34 trials for the three communication conditions, for a total of 204 trials each. Participants were fitted with the EEG electrodes prior to beginning the experiment which lasted about one hour.

In the cover story, two novel humanoid-like species were discovered in a fictitious NASA mission. They tended to have different faces types (wide, narrow) with friendly (good) or aggressive (bad) associations. “Good” face types represented positively-

valenced social associations while “bad” face types reflected a negative-social valence. Participants were expected to use face-type associations in the cover story to categorize each face, and then decide to act in accordance with the categorization: to defend themselves (from “bad” guys) or act friendly (to “good” guys). However, as in real life, not all faces were consistent with the associations presented in the cover story. Wide faces were randomly assigned to the “good” guy category in 60% of the trials and narrow faces were assigned to the “bad” guy category in 60% of the trials. Participants were informed about the probabilistic nature of the face-type associations using natural language, such as “tend to have” and “but this is not absolute.”

Given a preceding face categorization, rewards or punishments for the selected action also varied probabilistically. For faces categorized as a “bad” guy, 70% of the trials resulted in a reward for “defending,” and were punished otherwise. Likewise, for faces categorized as a “good” guy, 70% of the trials resulted in a reward for “defending,” and were punished otherwise. The probabilistic assignment for both face-type and action, introduced considerable uncertainty into both the categorization and decision processes. Because of this uncertainty, utilities were presumed to guide action selection (Wang & Busemeyer, 2016). Positive utilities applied to actions congruent with the preceding categorization whereas negative utilities applied to incongruent actions.

The key manipulation varied communication about the face’s category (see Figure 1). In the no-communication condition, no categorization information was provided before participants were asked to decide to take an action (attack, be friendly); instead,

the categorization process was presumed to occur implicitly (Townsend et al, 2001). In the self-expressing condition, participants categorized the face themselves. That is, they reported their beliefs about the face’s category membership. However, beliefs could change during prior to deciding to act, thus representing a degree of uncertainty for action selection (Wang & Busemeyer, 2016). In the received condition, the computer explicitly told the participants about the face’s category. Participants were instructed that the computer’s information was correct and were assumed to believe the categorization.

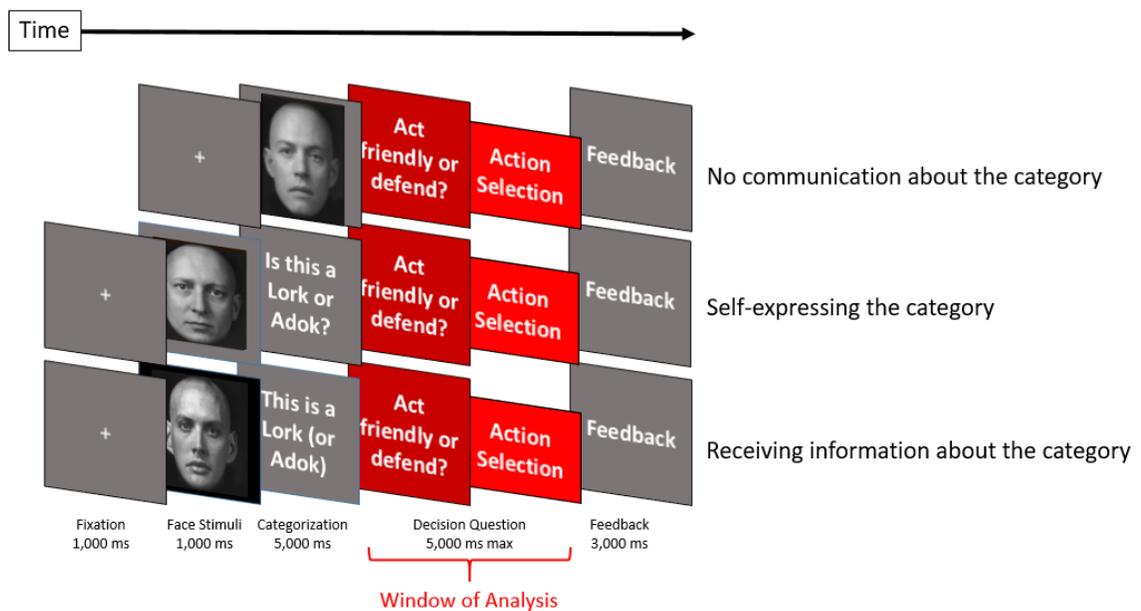


Figure 1. Experimental design. The key experimental manipulation varied communication about the face category. In comparison to no-communication, explicit communication (received, self-expressed) about the face category earlier in a trial was expected to modulate the superposition state and subsequent state revisions during the evaluation process immediately after being asked the decision question. Implicit categorization, presumed for the no-communication condition, was not expected to modulate information processing during the evaluation and served as the baseline of comparison for explicit communication (Townsend et al., 2000; Z. Wang & Busemeyer, 2016). The window of analysis, annotated by red brackets, begins after exposure to the decision question and concludes before receiving feedback. Though participants were

allowed five seconds to select an action, in 97% of the trials the task was completed within two seconds of being asked “Act friendly or defend?” Hence, the window of analysis after the decision question covers only the first two seconds.

EEG Data Acquisition and Preprocessing

EEG data was recorded continuously using a 64-channel BioSemi ActiveII system at a sampling rate of 512 Hz. The 64-electrode scalp placement used an elastic electrode cap (Electro-cap International, Inc.) corresponding to the 10–20 International System. Offline preprocessing was conducted using EEGLAB Toolbox (Delorme & Makeig, 2004) within the MATLAB environment. Data was epoched from -4500 ms to 2000 ms for each trial and time-locked to the decision question. This window preceded exposure to the face stimuli and concluded prior to the feedback events. Data was then down-sample to 256 Hz. Non-cerebral activity due to hand, body or eye movements, sinusoidal artifacts, and line and other environmental noise were removed through a multi-step process outlined by Cohen (2014b) and the EEGLAB Tutorial (Delorme & Makeig, 2004). For all participants, each trial was visually inspected and those containing large anomalous blocks of noise were manually rejected. A 1.0 Hz high pass filter was applied to the raw data to remove low frequency oscillations associated with biological functions such as sweat. Channels with data exceeding 3 standard deviations from average channel activity were removed using the EEGLAB “channel” function. The data was re-referenced to a common average. The CleanLine plugin was applied to remove fast oscillating line noise above 60Hz. An independence components analysis was conducted on the data using the *runica* algorithm (Delorme & Makeig, 2004). Independent components representing eye blinks, muscle artifacts, or other types of noise

were removed from the signal. After preprocessing, an average 58 trials per communication condition for each participant remained for hypothesis testing.

Time-Frequency Decomposition

To extract frequency band activity, the preprocessed EEG data were decomposed into their representations over both time and frequency, resulting in time-frequency representation (TFRs). Scripts for decomposition were coded manually in MATLAB and adapted from original scripts by Cohen (2014b) and Cohen (2015). The TFRs were obtained by computing the frequency band range (power spectrum) of the data through the fast Fourier transform function *fft* then multiplying the results by the power spectrum of complex Morlet wavelets ($e^{i2\pi f t} e^{-t^2/(2\sigma^2)}$), where t is time, i is a complex number, f is frequency, and σ defines the width of each frequency band (Cohen, 2014b). Specifically, f was set to range from 3-25 Hz in 20 logarithmically scaled steps. In order to achieve a satisfactory trade-off between temporal and frequency resolution, σ was set to range logarithmically from 3-10 cycles. The inverse of fast Fourier transform function *ifft* was then applied to produce TFRs in the time domain. To remove non-event related oscillatory activity from the data, power was normalized using a decibel (dB) transform ($\text{dB power} = 10 \times \log_{10}[\text{power}/\text{baseline}]$) relative to baseline neural activity. The baseline was computed from -800 ms to -400 ms before the onset of the decision event. We selected this range to avoid confounding the baseline neural activity with an observed increase in frontal alpha band power (8-12 Hz) from -400 to 150 ms which typically

reflects preparation for task performance (Bauer, Stenner, Friston, & Dolan, 2014; Min & Herrmann, 2007).

Outcome Measures

Our first dependent variable measured cognitive dissonance. Dissonance is defined as the conflicted and ambiguous feeling experienced during a superposition state when evaluating potential actions (Busemeyer & Bruza, 2012; Z. Wang & Busemeyer, 2016). We operationalized dissonance in two ways. First, dissonance was represented by conflict processing indexed by FM theta power. In previous work, FM theta has been modulated by exposure to a cue prior to a response (Gratton et al., 2018). Other research on neural activity suggests FM theta should also be modulated by utilities and social association valence (Falk & Scholz, 2018; Gabay et al., 2014; G. Wang et al., 2016). Based upon an all-conditions signal, FM theta power was computed for frequencies at 3-8 Hz from 150-450 ms after the decision event for each participant across all trials for each communication condition. Data for FM theta was provided from three midfrontal electrodes: Fz, FCz, and Cz (Cavanagh & Frank, 2014; Cohen & Cavanagh, 2011; Cohen & Van Gaal, 2013).

Second, dissonance was measured by the response time (RTs) for selecting an action. Conflict-oriented FM theta activity has been positively correlated with RTs, e.g., longer response times are associated with larger FM theta value (Cohen, 2014b). To increase the normality of the distribution, RTs were reciprocally transformed, $1/RT$ and

multiplied by 1,000 (Ratcliff, 1993), prior to analysis. To be consistent with epoch size for each trial, RTs over 2,000 ms were excluded from the analysis.

Our second dependent variable was a measure of state transition. According to the BAE model, the transition from a superposition state to a determinate state occurs during the evaluation process prior to a decision to act (Wang & Busemeyer, 2016). This process will be operationalized as parietal alpha band suppression indexing memory search and integration operations (Klimesch, 1999, 2012; Lam et al., 2016; Vassileiou et al., 2018). Increases in parietal alpha suppression index the amount of cognitive resources allocated to memory operations (Klimesch, 2012). The mean power in alpha suppression was computed for frequencies 9-25 Hz at 300-900 ms after decision event onset for each participant across all trials for each communication condition. Data was provided by electrodes Pz, POz, P1, P2, Pz, PO3, and PO4 (Cooper et al., 2016; Jiang et al., 2018; Lam et al., 2016; Vassileiou et al., 2018). A visual inspection of the time-frequency plots revealed considerable co-suppression of the beta band, 15-25 Hz so we expanded our frequency band range to include it in our analysis. This is not surprising since parietal beta band suppression frequently activates along with parietal alpha suppression during memory operations for semantic, rather than perceptual, stimuli (Clarke et al., 2018; Ohki & Takei, 2018; van Pelt et al., 2016; Vassileiou et al., 2018).

Chapter 3. Results

Frequency band power and response time data were imported into the R statistical environment (Team, 2014) and analyzed with the *lme4* package (Bates, Maechler, & Bolker, 2012). The *lme4* package was used to implement repeated-measures analysis of variances (ANOVAs) and conduct tests of normality. The *multcomp* package (Hothorn, Bretz & Westfall, 2008) was used for pairwise comparisons corrected with the Holm method. In all analyses and plots, data are time-locked to the onset of the decision question. Time-frequency plots were produced in MATLAB. Density function plots, scatterplots, and bar charts were produced in R using the *ggplot2* package (Wickham, 2016).

Electrodes for FM theta and parietal alpha regions, respectively, were clustered for an initial analysis. However, consistent with existing frequency band research (Billeke, Zamorano, Cosmelli, & Aboitiz, 2013; Cohen, 2014a; Cohen & Cavanagh, 2011), we present findings only for electrode FCz for FM theta power and POz for parietal alpha suppression as power was maximal over the two electrodes. The results from FCz and POz were consistent with the findings for the electrode clusters for FM theta power and the clusters for parietal alpha-beta suppression.

Prior to conducting our main analysis, we examined the effect of gender, age, and ethnicity on FM theta and parietal alpha activity. However, the effect of these covariates was not significant for both frequency bands and were not considered further. Further, the Shapiro-Wilk normality tests were non-significant for all analyses indicating the residuals were normally distributed and meeting an important assumption of ANOVAs.

Main Analysis

Our first hypothesis predicted that the absence of communication will result in more FM theta activity than either receiving information about the category or self-expressing it, and self-expressing will result in more FM theta activity than receiving information. A one-way ANOVA revealed a main effect of communication on FM theta power, $F(2, 62) = 17.93, p < 0.001$ (see Figure 2). Pairwise comparisons showed that average FM theta activity for the absence of communication ($M=0.89; SD=0.80$) was greater than receiving ($M=-0.04; SD = 0.81$), $p < 0.001$, and self-expressing ($M=0.83; SD = 0.82$) $p < 0.001$, and that FM theta activity was significantly greater for self-expressing than for receiving information, $p < 0.001$. Though the mean value for FM theta power after receiving communication was negative, it did not differ significantly from the baseline value of zero, $t(31) = -0.30, p = 0.76$. The results partially supported our first hypothesis. Receiving information and no communication exerted the expected effects on conflict processing as assumed by the BAE model. However, self-expressing a

category failed reduce more conflict processing than no-communication in contrast to our expectations.

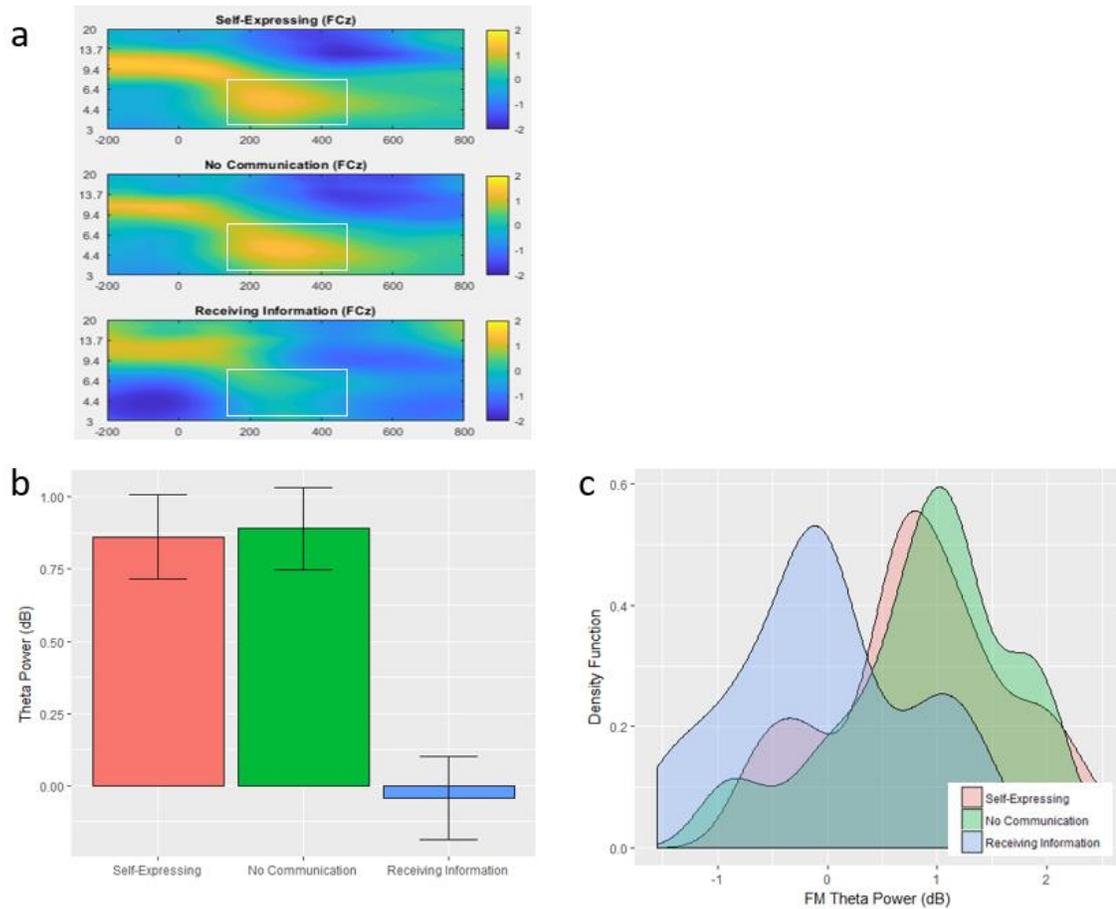


Figure 2. FM theta power for the three communication conditions – self-expressing, no communication, and receiving information. Mean FM theta power was computed at electrode FCz for frequencies at 3-8 Hz from 150-450 ms after the decision question for each participant across all trials for each communication condition relative to the baseline. (a) The white box denotes time and frequency band range for mean value computations. (b) FM theta power did not differ between self-expressing and no communication; but both differed significantly from receiving information; FM theta power for receiving information did not significant differ from zero (the baseline value).

Error bars denote standard errors. (c) Density function of the three communications reveals the sharp distinction in FM theta power for receiving information in comparison to the other communication conditions.

Based on the results for FM theta, we further explored our hypothesis about RTs and conflict processing. We predicted that no communication would result in longer RTs than self-expressing, and self-expressing would result in longer RTs than receiving information. The reciprocally transformed RTs were used in the analysis; however, raw RT values are reported in the statistical analysis and used in plots for ease of interpretation. We conducted a one-way ANOVA and found a main effect of communication on response times, $F(2, 62) = 44.89, p < 0.001$, such that in the absence of communication, ($M=788.02; SD = 262.14$), responses were slower than for self-expressing ($M=623.46; SD= 249.71$), $p < 0.001$, and for receiving information ($M=522.88; SD=143.90$), $p < 0.001$. RTs did not significantly differ between the two explicit communication conditions, though there was a trend in the predicted direction. See Figure 3 for details. The results provide partial support for our hypothesis and were consistent with the effect of communication on FM theta power for two communication conditions: received and none.

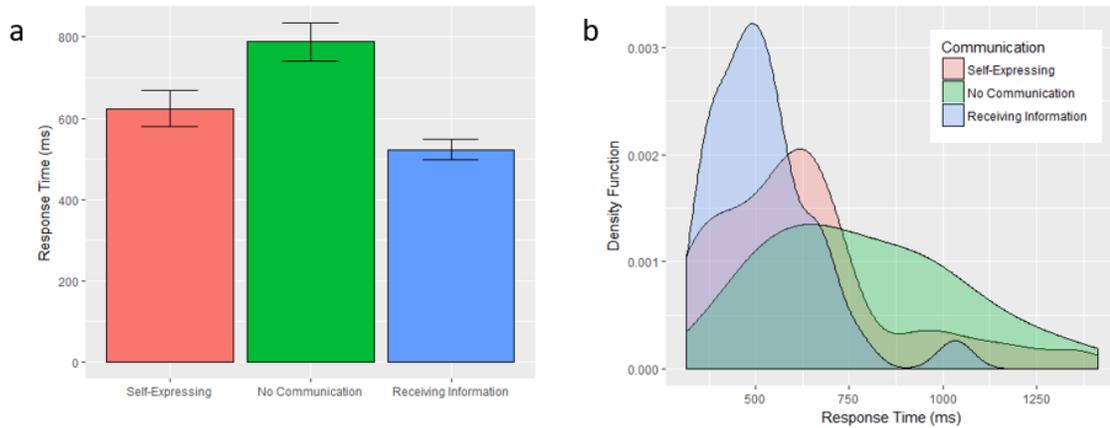


Figure 3. Response times for the three communication conditions – self-expressing, no communication, and receiving information. While reciprocally transformed RTs were used in the analysis, raw RT values are presented in the above plots for ease of interpretation. (a) RTs did not differ between self-expressing and receiving information; but both differed significantly from the absence of communication. Error bars denote standard errors. (b) Density function of the three communications reveals a unique distribution for each communication condition; in particular, receiving information exhibits the classic exponential shape of correct responses whereas no communication exhibits properties common to errors responses (Ratcliff, 1993).

Since RTs tend to positively associate with FM theta power (Cohen, 2014b), we conducted a correlation analysis. There was a significant positive Spearman correlation between RTs when pooling FM theta power across the three communication conditions, $r = 0.30$, $n = 96$, $p = 0.03$ (see Figure 4). Interestingly, when examined at the condition level, only FM theta for received communication was significantly correlated with RTs, $r = 0.38$, $n = 32$, $p = 0.03$. FM theta power for no communication and self-expressing was not significantly correlated with RTs.

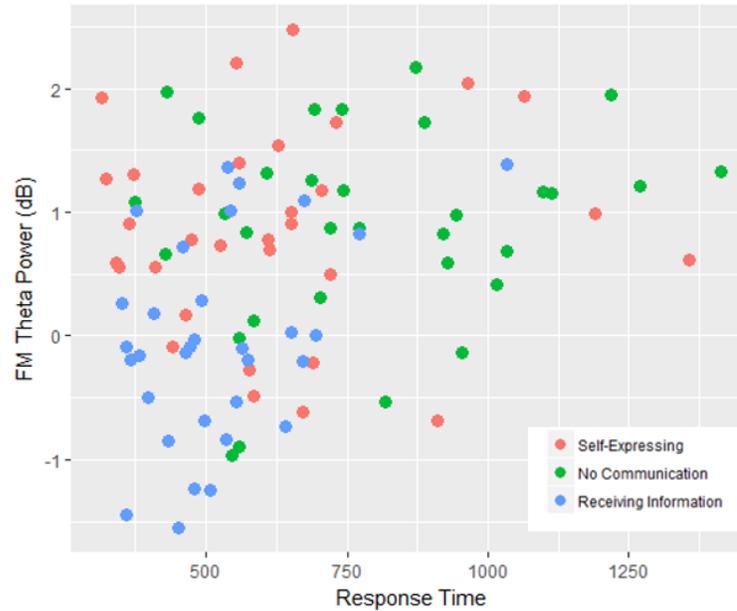


Figure 4. Response time-FM theta power scatterplot. Colored dots represent the three communication conditions – self-expressing, no communication, and receiving information. RTs and FM theta power were only significantly correlated for receiving information.

Our second hypothesis predicted that decisions with negative utilities would activate more FM theta power in comparison to decisions with positive utilities, reflecting increased dissonance for incongruent actions. Further, these results would vary by communication condition as predicted for H1. We first constructed a separate one-way ANOVA for a main effect of utilities on communication, and separate one-way ANOVAs for each negative and positive utilities. While there was not a significant main effect of utilities on FM theta power, the trend was in the predicted direction: decisions with negative utilities, ($M=0.50$; $SD= 1.43$), generated slightly more theta power than decision with positive utilities, ($M=0.47$; $SD= 1.11$), pooled across communication

conditions. When evaluating the effect of communication on actions with negative utilities, there was a main effect $F(2, 92) = 6.67, p < 0.001$. Pairwise comparisons revealed that FM theta power for no communication, ($M=0.84; SD= 1.51$), and self-expressing did not differ, ($M=0.86; SD= 1.51$), $p = n.s.$, but both self-expressing and no communication resulted in more FM theta power than receiving information, ($M=-0.22; SD= 1.42$), $p < 0.001$, respectively. There was also a main effect of communication for decisions with positive utilities, $F(2, 92) = 11.11, p < 0.001$. FM theta power did not differ between no communication ($M=0.69; SD= 1.08$), and self-expressing, ($M=-0.91; SD= 1.08$), did not differ, $p = n.s.$, but self-expressing and no communication resulted in more FM theta power than receiving information, ($M=-0.21; SD= 0.95$), $p < 0.001$, respectively. Figure 5 displays the time-frequency plots and dB power for FM theta. Notably, for both positive and negative utilities, the mean value of theta for receiving communication did not differ significantly from the baseline, or zero. While the results did not support H2 predictions for an effect of utilities, the pattern of FM theta activation

due to communication was consistent with the results for H1 as expected.

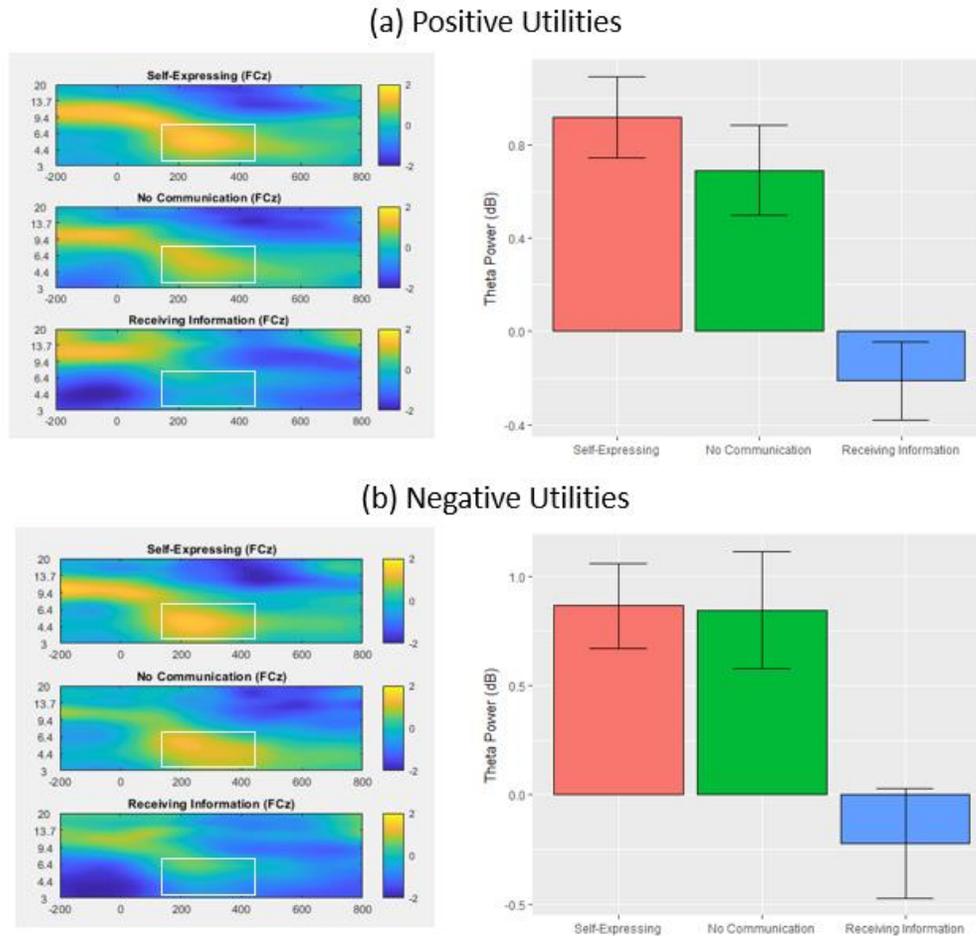


Figure 5. FM theta power for positive/negative utilities. Mean FM theta power was computed at electrode FCz for frequencies at 3-8 Hz from 150-450 ms after the decision question for each participant across all trials for each communication condition (self-expressing, no communication, and receiving information) relative to the baseline. The white box denotes time and frequency band range for mean value computations. FM theta power did not vary by positive or negative utilities but did vary by communication condition. (a) For positive utilities, FM theta power did not differ between self-expressing and no communication; but both differed significantly from receiving information; FM theta power for receiving information did not significantly differ from zero (the baseline value). Error bars denote standard errors. (b) For negative utilities, communication exerted the same effect on FM theta as for positive utilities.

Our third hypothesis predicted that self-expressing prior to selecting actions with negative utilities for positively valenced stimuli (good type faces) will activate more FM theta power than when selecting an action with negative utilities for negatively valenced stimuli (bad type faces). A one-way ANOVA did not reveal a significant difference in FM theta activity by stimuli valence, $p = \text{n.s.}$; however, the magnitude of FM theta power for stimuli valence was in the predicted direction: mean values for good type face ($M=0.90$; $SD=1.39$) were higher than mean values for the bad type face ($M=0.65$; $SD=1.24$; see Figure 6). The lack of significance could be due to the limited number of trials available for the analysis per participant per condition (good type face, $M = 10.59$, $\text{min}=3$, $\text{max}=19$; bad type face, $M = 11.97$, $\text{min}=4$, $\text{max}=18$). With limited trials, the noise inherent to EEG data and individual differences in frequency band peak and timing can obscure an existing cognitive effect, in part, due to oversensitivity to outliers (Cohen, 2014b). Though we cannot claim our hypothesis was supported, the direction of the findings provide modest and tentative support.

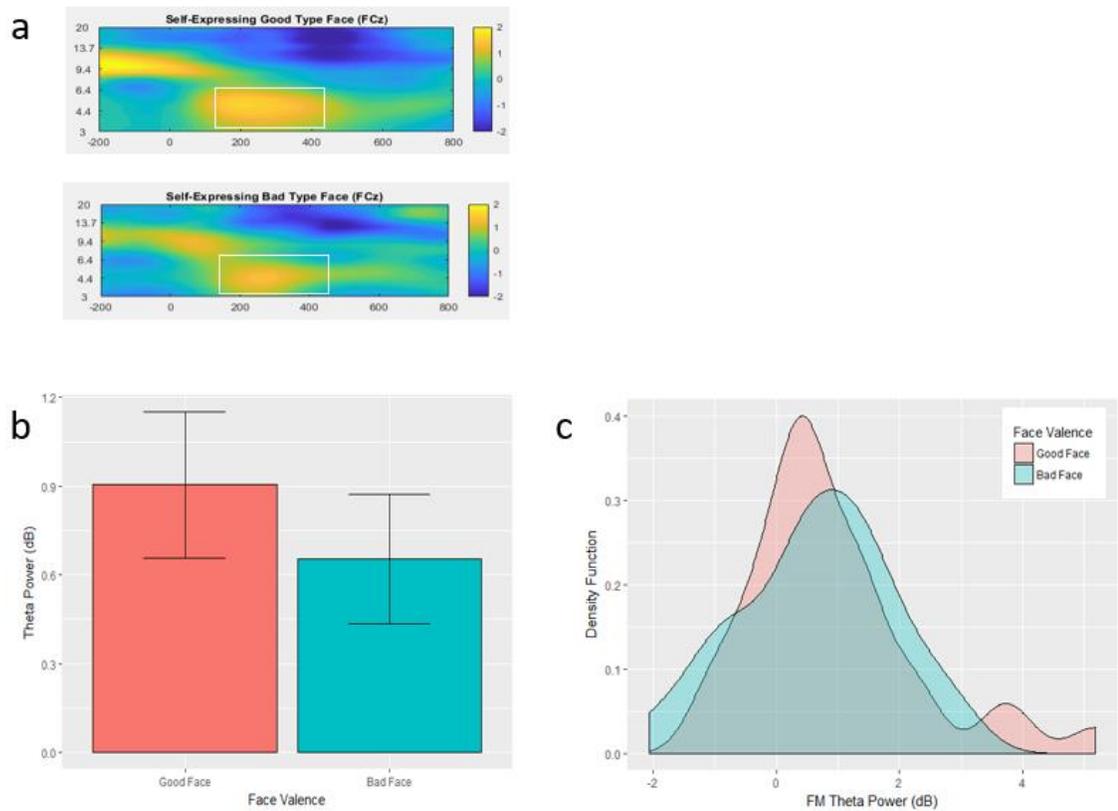


Figure 6. FM theta power for social stimuli with valenced associations. Images present FM theta power in self-expressing trials for actions with negative utilities for facial stimuli with a positive “good” or a negative “bad” valence. Mean FM theta power was computed at electrode FCz for frequencies at 3-8 Hz from 150-450 ms after the decision question for each participant across all trials relative to the baseline. (a) The white box denotes time and frequency band range for mean value computations. (b) FM theta power was greater for faces with a positive social valence in comparison to faces with a negative social valence; however, the difference was not significant. Error bars denote standard errors. (c) The density function reveals more variation in the higher FM mean values for positive “good” faces in comparison to “bad” faces suggesting a possible effect of outliers.

Our fourth hypothesis predicted that parietal alpha suppression, representing memory search and integration operations, would be modulated according to the following pattern: no communication will result in more alpha suppression (increased activation) than explicit communication about the category, and self-expressing will result in more alpha suppression than receiving information. The actual frequencies analyzed ranged from 8-25 Hz to include beta band suppression (see Figure 7). A one-way ANOVA revealed a main effect of communication on parietal alpha-beta suppression, $F(2, 62) = 15.34, p < 0.001$. Pairwise comparisons showed that alpha-beta suppression for the absence of communication, ($M=-1.60; SD =0.95$), was greater than for receiving information ($M= -0.42; SD =1.00$), $p < 0.001$, and self-expressing ($M=-1.01; SD =0.78$), $p < 0.005$; and suppression for self-expressing was significantly larger than for receiving information, $p < 0.005$. Hence, the results provide evidence for H4 about memory operations and state transitions as indicated by the BAE model.

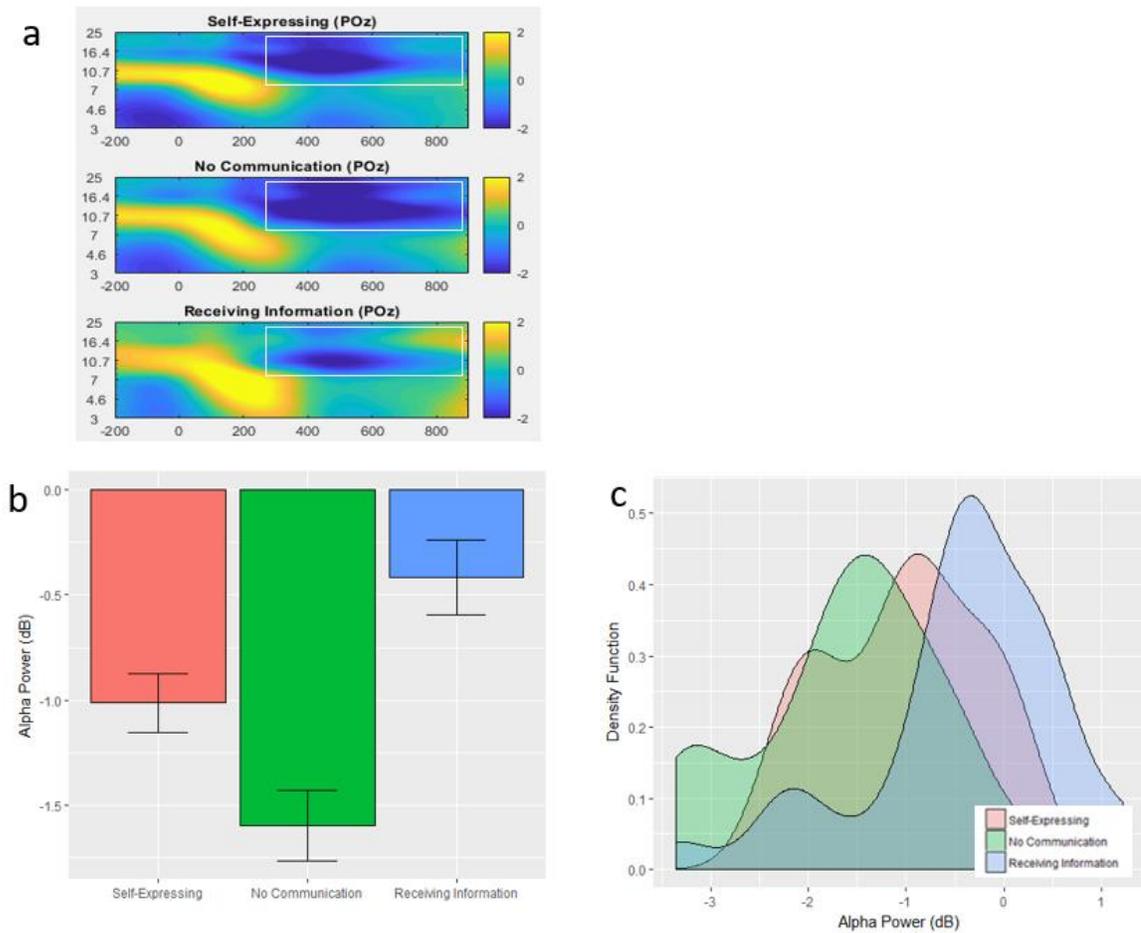


Figure 7. Parietal alpha-beta suppression for all three communication conditions. Mean alpha-beta suppression was computed at electrode POz for frequencies at 8-25 Hz from 300-900 ms after the decision question for each participant across all trials relative to the baseline. More suppression represents more resources allocated to memory processes. (a) The white box denotes time and frequency band range for mean value computations. (b) Alpha-beta suppression did not differ between self-expressing and no communication; but both differed significantly from receiving information. Error bars denote standard errors. (c) Density function of the three communications reveals a consistent distinction between the three communication conditions, as predicted.

Chapter 4. Discussion

The aim of the present study was to provide evidence for the mechanisms underlying the BAE model. Following the principles of QC theory, the BAE model proposes that communication acts as a measurement to interfere with evaluative processes prior to a decision (Busemeyer et al., 2009; Pothos & Busemeyer, 2009; Z. Wang & Busemeyer, 2016). Two key mechanisms were formalized in such QC models: (1) the superposition state which arises from dissonance or uncertainty when deciding between two or more actions, and (2) the transition from a superposition state to a determinate one during the action evaluation process. The evaluation of computational model mechanisms typically are through rigorous comparisons with competing computational models (Busemeyer & Bruza, 2012). The current study, however, directly examines frequency band activity in the brain with functions consistent with the two mechanisms in the BAE model. Overall, the neural evidence found in the current study are consistent with the BAE model while revealing some interesting complexity of the neural mechanisms.

The analysis of FM theta and parietal alpha frequency band activity provided limited support for effect of communication on these mechanisms. Our analysis of conflict processing, as indexed by FM theta activity, offered initial evidence that

communication resolves the superposition state conceptually similar to a wave function collapse in quantum mechanics (Bruza et al., 2015; Busemeyer & Bruza, 2012; Z. Wang & Busemeyer, 2016). Further, parietal alpha-beta suppression provided support for the proposition that communication modulates the evolution of an entangled cognitive system through the time of decision.

The influence of communication on the superposition state, as conceived by QC theory, was most evident after receiving explicit information. The BAE model predicts that receiving information, in comparison to the absence of communication, resolves more dissonance about the decision (Z. Wang & Busemeyer, 2016). With the category known, dissonance was expected only for the decision about potential actions. However, our results suggest that very little conflict processing took place. That is, being informed of the category appeared to resolve conflict about the action – a stronger effect than assumed by the BAE model. Even so, this result is consistent with the idea that communication acts as a measurement to “break” an entangled system. On the other hand, without knowing the category, considerably more conflict processes occurred, suggesting the presence of a cognitive state conceptually analogous to a superposition state. While we cannot say definitively that conflict emerged from uncertainty across potential categories and actions, it is plausible and consistent with BAE model assumptions about a superposition state.

Communication similarly dominated conflict processing when including utilities in the analysis. In contrast to our second hypothesis, utilities failed to moderate the

superposition state; however, communication exerted the same pattern of effects on FM theta, in general, for both positive and negative utilities. This is surprising since incongruent trials, associated with negative utilities in the BAE model, consistently enhance neural activations in the conflict processing research (Cohen & Donner, 2013; Cohen & Van Gaal, 2013; Cooper et al., 2016; Gratton et al., 2018; Jiang et al., 2018). Nonetheless, a handful of studies either revealed diminished or no difference in conflict processing for incongruent trials, depending upon the cue and the task (Aarts, Roelofs, & van Turennout, 2008; Alpay, Goerke, & Stürmer, 2009; Strack, Kaufmann, Kehrer, Brandt, & Stürmer, 2013; van Driel et al., 2015). For example, an informative cue eliminated conflict-related activation in the ACC during subsequent evaluative processing, irrespective of target congruency in comparison to a non-informative cue (Aarts, et al., 2008). Similar to the concept of communication-as-measurement, the informative cue resolved conflict processing prior to the evaluation stage. The reduction in conflict processing reflects the responsiveness of top-down, controlled processes to certain information (Aarts et al., 2008; van Driel et al., 2015).

Taking the inverse of this logic, sensitivity to utilities should be heightened in absence of communication when certainty about the category and action was low. However, our results revealed no significant difference between negative and positive utilities for either self-expressing or no communication. The absence of an effect may be due to the probabilistic nature of the category and action. In our study, probability of the stimuli category as described in the cover story was set to 60% and the probability of the

action, given the category, was set to 70% across the three communication conditions. Under such uncertainty, both positive and negative utilities may be co-activated during the evaluation process with neither producing an advantage for enhanced sensitivity to conflict. Indeed, a recent study using a mixed-gambling task, utilities similarly failed to moderate conflict processing when the alternatives were not clearly differentiated (Pornpattananankul, Grogans, Yu, & Nusslock, 2019). From the QC theory perspective, more definitive information about beliefs and actions may be required for utilities to influence an entangled system.

Self-expressing also failed to modulate conflict processing as unexpected. Since the category was uncertain but made explicit, we predicted self-expressing would resolve more conflict than the absence of communication but less receiving information. We interpreted the observed lack of resolution as continued indecision over potential categories and potential actions during the evaluation. Unlike being informed of category, self-expressing appeared to convey no more certainty about the category than the implicit categorization assumed in the absence of communication.

Our results provide new insights for self-expressing research, also known as self-effects. In behavioral studies, the act of expressing a belief typically *increases* certainty about it and induces related behavioral outcomes. The strengthening of beliefs has been observed in health communication (Geusens & Beullens, 2019; Han et al., 2008; Shaw, Hawkins, McTavish, Pingree, & Gustafson, 2006), on and offline political deliberation (Cho, Ahmed, Keum, Choi, & Lee, 2018; Eveland, 2004), perceived mathematical

efficacy (Canning & Harackiewicz, 2015), mediated communication and self-concept (Walther et al., 2011), and environmental behaviors (Aronson, 1999). The influence of self-effects have been attributed to constructive message production and elaboration (Eveland, 2004; Pingree, 2007). During spontaneous expressing and message composition, thoughts are constructed from existing representations stored in memory *and* from new ways of thinking about the topic –regardless of the expectations about the receiver. Because constructive processes reveal thoughts beyond pre-existing beliefs, Pingree (2007) argues that self-expressing leads to inferences about one’s own attitudes and beliefs in accordance with Bem’s (1967) self-perception theory. That is, “if I say or write it, then I must be revealing something important about myself.” Though self-perception theory explains increases in belief strength, it does not predict the cognitive dissonance (and conflict processing) observed after self-expressing in our data and formalized by the BAE model for stimuli with positive social associations (Busemeyer et al., 2009; Pothos & Busemeyer, 2009; Z. Wang & Busemeyer, 2016)

On the other hand, self-persuasion theory views cognitive dissonance as central to self-expressing (Aronson, 1999; Valkenburg, 2017; but see Brinol et al., 2012 for an alternate perspective). Specifically, overt behavior inconsistent with existing beliefs leads to subsequent expressions shifted to be aligned with the behavior. The internal discomfort caused by a misalignment between behavior and beliefs motivates a post *hoc shift* in beliefs (Festinger, 1957), and this shifts are evident in self-expressions. For example, participants instructed to engage in unfriendly behavior during an online

conversation subsequently expressed unattractive perceptions of their partner (Walther, Van Der Heide, Tong, Carr, & Atkin, 2010). In a video game study, filling the role of a Palestinian or Israeli leader subsequently resulted in negative reports of the opposing group (Alhabash & Wise, 2015).

Self-persuasion theory is consistent with Festinger's (1957) temporal view of cognitive dissonance: people align their beliefs to be consistent with their actions. From the communication perspective, the action *precedes* the shift in self-expression. However, the BAE model predicts an inverse temporal relationship: cognitive dissonance occurs *after* self-expressing and before the decision. The FM theta activity in our study provides support for this prediction. Predecisional conflict is also consistent with the biosocial model of affective decision making (Kitayama & Tompson, 2015). Like the BAE model, the biosocial model assumes dissonance emerges during deliberation about two alternatives. However, self-expression – or an effect due to measurements in any form -- was not considered in the model. Ultimately, neither self-persuasion theory nor the biosocial model sufficiently explain the pattern of FM theta activation observed in our study. While self-persuasion theory accounts for a relationship between dissonance and self-expressing, it occurs in the opposite causal direction. Conversely, while biosocial model builds upon evidence for predecisional dissonance reduction, it does not assert a role for self-expressing in the process. Notably, we do not claim that cognitive dissonance does not emerge post-decisionally; indeed, neural evidence exists to support this claim (Colosio, Shestakova, Nikulin, Blagovechtchenski, & Klucharev, 2017; Fischer

et al., 2013). Rather, our interest lies in investigating how self-expressing influences cognitive dissonance as assumed by the BAE model and as revealed by our analysis.

Indeed, our third hypothesis articulated a nuanced but important effect of self-expression on the cognitive system. Pingree (2007) argues that without a receiver in mind, the sender is mentally absolved of “social sanctions.” However, the BAE model assumes that irrespective of the self-reported category, making a decision with a positive association leads to more dissonance than an incongruent decision for a negative association. The implication is that normative expectations for social associations, e.g., stereotypes and biases, exert influence across the decision process; self-expressing does not necessarily resolve it. Our analysis provided modest tentative support for this prediction (Townsend et al., 2000; Z. Wang & Busemeyer, 2016). Though self-expressed communication was one-way – there was no recipient for the category information – social implications appeared to influence the evaluation process. Numerous studies using neural data have validated the importance of positive social associations. Falk & Scholz (2018) found a robust effect for the maintenance of social connections during an extensive review of neural structures and the value system. For example, activity in the relevant structures increased for stimuli positively rated by peers in comparison to negatively rated stimuli (Falk & Scholz, 2018; Mason et al., 2009). Separately, a study using the Ultimate Game paradigm, event-related-potentials (ERPs) associated with conflict process increased after the proposer made an offer advantageous to the self but unfair to the opponent (G. Wang et al., 2016).

Further, the *mere* possibility of deciding to behave inconsistently with existing beliefs, especially for positive social associations, may explain the lack of difference in dissonance reduction between self-expressing and the absence of communication, in general. Because of the low power for self-expressing for faces with negative utilities, we were not able to make a definitive claim for this proposition. Nonetheless, the neural evidence supporting BAE model predictions and our unexpected findings increase our knowledge of self-expressing and related information processing. Specifically, we potentially make a novel contribution to the self-effects literature about *how* and *when* self-expressing influences cognitive dissonance beyond explanations by self-persuasion theory (Aronson, 1999; Valkenburg, 2017), the biosocial model (Kitayama & Tompson, 2015), and other models of sender influences on the self (Eveland, 2004; Eveland, Morey, & Hutchens, 2011; Pingree, 2007),

Evidence for our fourth hypothesis further strengthens the case for the mechanisms specified by the BAE model. Specifically, being informed of a category resulted in fewer resources allocated to memory operations, as indexed by parietal alpha-beta band suppression, than self-expressing or the absence of communication, and self-expressing resulted in less resource allocation than no-communication. The inclusion of parietal beta band suppression in our analysis was not surprising since it often co-activates with alpha band during semantic memory operations. For example, alpha-beta suppression was observed during the encoding of relationships between words presented in strings (Vassileiou et al., 2018), the integration of new words into a sentence (Lam et

al., 2016), and better memory for face pairs with designated *a priori* relationships (Mölle et al., 2002). Increases in suppression occurred as single elements (words, faces, symbols, etc.) were encoded into or retrieved from memory then integrated into a coherent meaningful representation. By contrast, exposure to scrambled or random elements produced minimal, if any, suppression. These findings are consistent with our results and BAE model assumptions about the evolution of an entangled cognitive system during the evaluation process (Wang & Busemeyer, 2016). When neither the category nor the action were known, more resources were required to form the representation used in the decision from the many potential possibilities.

Alternate Explanations

FM theta activation. While communication in general exerted the hypothesized effect on FM theta power and parietal alpha-beta suppression based upon the underlying processes of the BAE model, other functions of these frequency bands may have accounted for the observed activity. Cavanaugh & Frank (2014) view FM theta as the *lingua franca* for implementing adaptive control across diverse circumstances to include response to surprise, error detection, and working memory operations. Given our experimental design, it is not likely that surprise modulated FM theta activity. While error-processing was plausible, our data suggest increases in FM theta activity resulted from conflict about the response (Cohen, 2014b; Cohen & Van Gaal, 2013). In particular, error-related theta peaks after the decision whereas conflict-related theta peaks prior to the decision – which is what we observed in our data. Further, error-related theta

is negatively correlated with response time whereas on conflict-related theta exhibits a positive correlation. While results for the correlation analysis was mixed, response time predicted FM theta power in our analysis of variance. On the other hand, it is more difficult to rule out the contribution of working memory operations to FM theta activity. However, memory-related theta in the frontal medial region tends to activate 500 ms after stimuli onset (Kawasaki & Yamaguchi, 2013; Solomon et al., 2017) whereas FM theta in our study decayed at 450 ms on average. Notably, we distinguish memory related FM theta from working memory-related theta in the occipital-parietal region (Li et al., 2017) which exhibited a robust signal irrespective of communication condition. Though we cannot not definitively eliminate working memory activity as a partial or full explanation of FM theta activation, the behavior of the frequency band was nonetheless consistent with the contexts producing conflict processing (Cohen & Donner, 2013; Cohen & Ridderinkhof, 2013; Cohen & Van Gaal, 2013; Gratton et al., 2018; Jiang et al., 2018; van Driel et al., 2015).

Parietal alpha-beta suppression. Beyond the release of attention and integration of representations in memory, the cognitive function of alpha-beta suppression remains under debate (Mazaheri et al., 2018; Singer, 2018). One perspective views suppression as an index of working memory only (Lenartowicz, Escobedo-Quiroz, & Cohen, 2010; Vassileiou et al., 2018) while another perspective assumes the integration of representations across both working and long-term memory (Clarke et al., 2018; Hanslmayr, Gross, Klimesch, & Shapiro, 2011; Klimesch, Sauseng, & Hanslmayr, 2007).

Our study does not resolve this issue. Further, alpha-beta suppression in parietal region electrodes may reflect additional cognitive functions such as a general attention mechanism (Cohen & Ridderinkhof, 2013), motor control and response selection (Cohen & Van Gaal, 2013; Jiang, Zhang, & Van Gaal, 2015), or preparation for an upcoming trial (Cooper et al., 2016; van Driel et al., 2015). While our experimental design allows us to rule out motor control and response selection as a possible explanation for alpha-beta suppression, we do not have the tools to evaluate the contribution of other potential functions to the observed data. Since these alternate explanations cannot be ruled out, we additionally cannot be fully confident that the observed parietal alpha-beta activity provided evidence for the relationship between communication and our assumptions about uncertainty reduction during the evolution of the cognitive state.

Is conflict processing the same as cognitive dissonance? So far, we have assumed that conflict processing, indexed by FM theta, conceptually corresponds to cognitive dissonance as assumed by the BAE model. But can we be certain conflict processing and cognitive processing share properties sufficiently enough to be viewed as the same construct or highly overlapping constructs? Research using FM theta activity to represent does not explicitly relate conflict processing to cognitive dissonance. Instead, we viewed conflict emerging from competition between prepotent or congruent versus incongruent responses as the primary link. However, empirical investigations typically use perceptual or low-level cognitive stimuli to investigate conflict processing; by contrast, cognitive dissonance assumes conflict involving high-level constructs, such as beliefs or attitudes.

Given this distinction, can we rely on modulations of FM theta to provide evidence for the BAE model mechanisms?

The biosocial model addresses this issue directly (Kitayama & Tompson, 2015). Based findings from fMRI and ERP studies, the authors concluded that dissonance emerges from events not necessarily associated with the sophisticated representations inherent to beliefs or attitudes. For example, both nonhuman animals without higher order cognition and humans with impaired episodic memory lack the cognitive machinery to form complex beliefs, yet they nonetheless exhibit dissonance during difficult decisions.

Inzlicht, Batholow, and Hirsh (2015) make an even stronger argument for the similarity between cognitive dissonance and conflict processing. Indeed, in their view, the primary function of cognitive control is to manage conflict. An extensive review of the cognitive control literature revealed that the co-activation of competing mental representations leads to conflict during decision processing. Further, this conflict reflects an aversive state matching the properties of cognitive dissonance. Similar to Kitayama & Thompson (2015), they found that the aversive state arose when tasks “threatened cherished goals” and when decisions involved low-level cognitive tasks requiring simple responses. Taken together, these two perspectives lend support for the use of conflict processing, and related FM theta activity, as evidence of the superposition state and its sensitivity to measurement via communication.

However, both the biosocial model (Kitayama & Tompson, 2015) and Inzlicht et al (2015) view emotion, not cognition, as the genesis of conflict processing and cognitive dissonance, though each conceives it in different ways. The biosocial model asserts that the desire for appetitive outcomes drives dissonance reduction. On the other hand, Inzlicht et al (2015) argue that negative emotions dominate the emergence of conflict processes, though these emotions tend to be transient and easily resolved with the decision. While valenced utilities and face associations can be construed as consistent with the influence of emotions on the superposition state and state transitions, BAE model does not explicitly acknowledge a core role of emotionality on dissonance emergence or reduction.

Limitations and Recommendations for Future Research

Our study had several limitations. We evaluated a single time-window within a larger temporal landscape. The evaluated window – comprising the period immediately preceding the decision question and extending through the decision arc – was selected for three main reasons: (1) the event was equivalent across all three communication conditions; (2) hence, reflected the cognitive processes influenced by exposure (or not) to earlier category information; and (3) presumably contained two central mechanisms modulated by communication as assumed by the BAE model – the superposition state and the transition to a determinate state at the time of decision (Busemeyer et al., 2009; Pothos & Busemeyer, 2009; Z. Wang & Busemeyer, 2016). By constraining ourselves to this window, we were not able to evaluate the effect of communication about the

category – from either the receiver’s or sender’s perspective – on the cognitive state. Such an analysis would increase our understanding of dynamic interactions between communication type, category congruency, and subsequent evaluations of potential actions – an approach especially important to understanding the nature of entanglement in cognitive systems (Busemeyer & Bruza, 2012). We also did not evaluate the cognitive state after participants were provided feedback. The impact of feedback on subsequent decisions has been a major focus area for research on value systems, expected utilities, and the effect of rewards and punishment as they manifest in the brain. While some studies focused solely on the window surrounding feedback, many other studies took a dynamic approach and evaluated the impact of feedback on subsequent trials (Balconi & Vanutelli, 2018; Billeke et al., 2013; Cohen & Donner, 2013; Colosio et al., 2017; Glazer, Kelley, Pornpattananangkul, Mittal, & Nusslock, 2018; Jiang et al., 2018; van Driel et al., 2015). Indeed, the behavioral studies testing the BAE model included estimates for the entire categorization-decision process – from exposure to stimuli through feedback. However, hundreds of participants participated in each of these studies. By comparison, only 32 participants completed our study; given the complexity of our study design, we lacked the power to conduct an extensive, dynamic analysis of all the plausible combinations influencing the proposed underlying mechanisms. Since EEG studies are time-consuming to implement, future studies may benefit from implementing pared down versions of the BAE model as a way to gain enough power for a dynamic analysis across the entire affected temporal window.

Our study design did not allow us to distinguish the effect of communication on the superposition state and state transitions from other possible contributing functions. For example, random word lists and scrambled faces routinely fail to induce conflict processing, as indexed by FM theta activity, and integrations in memory, as indexed by parietal alpha-beta suppression (Lam et al., 2016; Mölle et al., 2002). The inclusion of “meaningless” stimuli in futures tests of BAE model mechanisms could help isolate the effect of utility valence or entanglement of categories-and-actions on neural oscillations.

Further, BAE model predictions informally guided our hypothesis formation. Our hypotheses were quite general and used only a single data for each participant for each communication condition. The advantage of computational models of cognition, particularly a model introducing a powerful mathematical formalism based on quantum probability, is that they make predictions otherwise unobservable in non-computational theories or models by the inclusion of model parameters for the underlying functions. Further, neural activity occurs at multiple temporal and spatial scales, and are not necessarily linear. Constructing a computational model of the brain that uses the parameters of cognitive computational models to predict neural activity may yield a more nuanced yet unambiguous understanding of underlying psychological processes not fully observed in the present study (De Hollander et al., 2016; Love, 2016; Palmeri et al., 2017).

Finally, as analyzed in our study, frequency band activity provided tangible yet limited information about cognitive states; hence, the findings may also extend to other

explanations of uncertainty reduction beyond the BAE model. For example, the Markov model compared with the BAE model in Wang & Busemeyer (2016) assumed that individuals are in one state at a time with respect to a belief and follow a determinate trajectory towards a decision. By comparison, the BAE model assumes people are superimposed, not determinate, across the potential beliefs. The observed FM theta activation cannot be interpreted to differentiate between a psychological state following a single trajectory amidst co-activated alternatives versus a state evolving across them over time. To be fair, however, existing behavioral evidence suggests differences in dissonance may exist between the two models. For example, when Busemeyer et al (2009) included a dissonance parameter in the Markov model, it did not improve model predictions relative to the data and to the BAE model. Clarifying Markov model assumptions about competing potential beliefs may help quantify expected dissonance in the future. For the present, we assume that making a difficult decision among competing responses – whether a single trajectory is followed or not – would result in the recruitment of resources for conflict processing. Under such an assumption, our findings are supportive but not necessarily unique to quantum cognition.

Conclusion

Our analysis of frequency band power provided initial and limited support for the effect of communication on the proposed underlying mechanisms of the BAE model, a computational model based on quantum cognition and the mathematical formalism of quantum mechanics (Busemeyer et al., 2009; Z. Wang & Busemeyer, 2016). In

particular, receiving certain information resolved the conflicted internal state conceptualized as a superposition state by the quantum cognition theory. We unexpectedly found that self-expressing generally did not resolve conflict more than the absence of communication, and hence provided novel insights about the effects of sender effects and cognitive dissonance. Communication, in general, exhibited a similar effect on the evolution of the cognitive state as represented by resources allocated to memory search and integration operations. While these findings are not unique to the BAE model, per se, they are the first to offer evidence for underlying psychological mechanisms previously only explored in computational models.

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Appendix 1. MATLAB Script for Time-Frequency Decomposition

```
% Script for time-frequency decomposition and mean cross-trial power
% for channels FCz and POz
% Adapted from scripts provided by Cohen (2015) and Cohen (2014b)

%% load file with data for all 32 subjects
load allSub.mat;

%% declare parameters that will be the same for all conditions

% assign number of subjects for loops
subcount = length(allSub);

% find indices of start and end times -100 to 1000ms
% since all subjects have same time window, variable can be declared
% using any subject
useTimes = dsearchn(allSub(1).EEG.times', [-1000 1000]');

%create a new vector of the time window
newTime = allSub(1).EEG.times(useTimes(1):useTimes(2));

% create time points variable for easier matrix creation later
pnts = length(newTime);

% define frequency and s parameters
srate = allSub(1).EEG.srate;
time = -1:1/srate:1; % time in seconds

%define frequency range
minF = 3;
maxF = 25;
% number of frequencies
numF = 20;

% create frequency range
frex = logspace(log10(minF), log10(maxF), numF);

%create cycle variable
s = logspace(log10(3), log10(10), numF) ./ (2*pi.*frex);

%get indices of baseline period
baseline = dsearchn(newTime', [-800 -400]');
```

```

% declare communication condition types
types = [25 26; 36 37; 50 52]; %self-expressing, no communication,
receiving information

% create 2 zeros matrices to store all the averaged data from each
channel.
FczAll = zeros(numF,pnts, length(types));
PzAll = zeros(numF,pnts,length(types));

% declare matrix for mean values to export
% for FCz
fczsubset = zeros(subcount,length(types));
cuttime = dsearchn(newTime',[150 450]');
% for POz
pzsubset = zeros(subcount,length(types));
cuttimep = dsearchn(newTime',[300 900]');

%% Fcz time-frequency decomposition over three communication conditions

% declare which channel to pull from
chan2use = 'FCz';

% Loop over conditions, then subjects, then frequencies
for t=1:length(types)

    %select the condition to use
    type = types(t,:); % comma, colon instructs to capture both first
and second column
    %original code type = types(t) captured first col only

    %declare zeros matrix to store all subjects before averaging
    eegpower = zeros(numF,pnts,subcount);

    %loop over subjects
    for su=1:subcount

        % assign subject
        subject = allSub(su).EEG;

        % create matched matrix of events and epochs
        type_epoch = [subject.event(:).type;subject.event(:).epoch];

        % get the list of epochs
        epochs2use =
type_epoch(2,find(ismember(type_epoch(1,:),type)));

        fczcond(t,su) = length(epochs2use); %trial counts for each
subject per cond

```

```

% pull data
data =
squeeze(subject.data(strcmpi(chan2use,{subject.chanlocs.labels}),useTimes(1):useTimes(2),epochs2use));

%reshape into one concatenated file for convolution
dataCat = reshape(data,1,[]);

% count number of trials
trialcnt = length(epochs2use);
trialscount_FCz(t,su) = trialcnt;

% prepare data for convolution
nData = length(dataCat);
nKern = length(time);
nConv = nData + nKern -1;
halfWave = (nKern-1)/2;

n_conv_pow2 = pow2(nextpow2(nConv));

fftdata = fft(dataCat, n_conv_pow2);

%loop over frequencies
for fi=1:length(frex)

    % make wavelets
    wavelet = exp(2*pi*li*frex(fi).*time) .* exp(-
time.^2./(2*s(fi)^2));
    wavelet = fft(wavelet, n_conv_pow2);
    wavelet = wavelet./max(wavelet);

    %perform convolution via ifft
    eegconv = ifft(wavelet.*fftdata);
    eegconv = eegconv(1:nConv);
    eegconv = eegconv(halfWave+1:end-halfWave);

    % extract power
    power_data_raw = abs(eegconv).^2;
    power_data_raw = reshape(power_data_raw,pnts,trialcnt)';

    eegpower(fi,:,su) = mean(power_data_raw);

end

%baseline computation then dB convert
baseline_power =
squeeze(mean(eegpower(:,baseline(1):baseline(2),su),2));
eegpower(:, :, su) = 10*log10(
squeeze(bsxfun(@rdivide,eegpower(:, :, su),baseline_power) ));

end

```

```

%average subjects together and store in Fcz matrix
FczAll(:, :, t) = mean(eegpower, 3);

%pull mean data for export
for i=1:subcount
    fczsubset(i, t) = mean(mean(eegpower(1:9, cuttime(1):cuttime(2), i)))
end

end

% total number of trials per participant
fczcond_ct(4, :) = sum(fczcond); %declare 4th row to sum across col

%% POz time-frequency decomposition over three communication conditions

% declare which channel to pull from
chan2use = 'POz';

% Loop over conditions, then subjects, then frequencies
for t=1:length(types)

    %select the condition to use
    type = types(t, :);

    %declare zeros matrix to store all subjects before averaging
    eegpower = zeros(numF, pnts, subcount);

    %loop over subjects
    for su=1:subcount

        % assign subject
        subject = allSub(su).EEG;

        % create matched matrix of events and epochs
        type_epoch = [subject.event(:).type; subject.event(:).epoch];

        % get the list of epochs
        epochs2use =
type_epoch(2, find(ismember(type_epoch(1, :), type)));

        % pull data
        data =
squeeze(subject.data(strcmpi(chan2use, {subject.chanlocs.labels}), useTimes(1):useTimes(2), epochs2use));

        %reshape into one concatenated file
        dataCat = reshape(data, 1, []);

        % count number of trials
        trialcnt = length(epochs2use);

```

```

    trialscount_Pz(t,su) = trialcnt;
    % prepare data for convolution
    nData = length(dataCat);
    nKern = length(time);
    nConv = nData + nKern -1;
    halfWave = (nKern-1)/2;

    n_conv_pow2 = pow2(nextpow2(nConv));

    fftdata = fft(dataCat, n_conv_pow2);

    for fi=1:length(frex)

        % make wavelets
        wavelet = exp(2*pi*1i*frex(fi).*time) .* exp(-
time.^2./(2*s(fi)^2));
        wavelet = fft(wavelet, n_conv_pow2);
        wavelet = wavelet./max(wavelet);

        %perform convolution via ifft
        eegconv = ifft(wavelet.*fftdata);
        eegconv = eegconv(1:nConv);
        eegconv = eegconv(halfWave+1:end-halfWave);

        % extract power
        power_data_raw = abs(eegconv).^2;
        power_data_raw = reshape(power_data_raw,pts,trialcnt)';

        eegpower(fi, :, su) = mean(power_data_raw);

    end

    %dbconvert power
    baseline_power =
squeeze(mean(eegpower(:,baseline(1):baseline(2),su),2));
    eegpower(:, :, su) = 10*log10(
squeeze(bsxfun(@rdivide,eegpower(:, :, su),baseline_power) ));

    end
    %average all subjects together and store result in Pz matrix
    PzAll(:, :, t) = mean(eegpower,3);

    %pull mean data for export
    for i=1:subcount
        pzsubset(i,t)=
mean(mean(eegpower(10:20,cutttimep(1):cuttimep(2),i)))
    end
end

%% Plot results
%shorten time window in plot for clarity

```

```

ptimes = dsearchn(newTime', [-500 800]');
plotTime = newTime(ptimes(1):ptimes(2));

% Fcz
figure(1)
subplot(311)
contourf(plotTime, frex, FczAll(:, ptimes(1):ptimes(2), 1), 40, 'linecolor', '
none')
set(gca, 'clim', [-2 2], 'xlim', [-500
800], 'yscale', 'log', 'ytick', logspace(log10(minF), log10(maxF), 6), 'ytickl
abel', round(logspace(log10(minF), log10(maxF), 6)*10)/10)
colorbar
title('Self-Expressing (FCz)')
subplot(312)
contourf(plotTime, frex, FczAll(:, ptimes(1):ptimes(2), 2), 40, 'linecolor', '
none')
set(gca, 'clim', [-2 2], 'xlim', [-500
800], 'yscale', 'log', 'ytick', logspace(log10(minF), log10(maxF), 6), 'ytickl
abel', round(logspace(log10(minF), log10(maxF), 6)*10)/10)
colorbar
title('No Communication (FCz)')
subplot(313)
contourf(plotTime, frex, FczAll(:, ptimes(1):ptimes(2), 3), 40, 'linecolor', '
none')
set(gca, 'clim', [-2 2], 'xlim', [-500
800], 'yscale', 'log', 'ytick', logspace(log10(minF), log10(maxF), 6), 'ytickl
abel', round(logspace(log10(minF), log10(maxF), 6)*10)/10)
colorbar
title('Receiving Information (FCz)')

figure(2)% all communication conditions spectrogram for FCz
contourf(plotTime, frex, FczAll(:, ptimes(1):ptimes(2)), 40, 'linecolor', 'no
ne')
set(gca, 'clim', [-2 2], 'xlim', [-500
800], 'yscale', 'log', 'ytick', logspace(log10(minF), log10(maxF), 6), 'ytickl
abel', round(logspace(log10(minF), log10(maxF), 6)*10)/10)
colorbar

% POz
figure(3)
subplot(311)
contourf(plotTime, frex, PzAll(:, ptimes(1):ptimes(2), 1), 40, 'linecolor', 'n
one')
set(gca, 'clim', [-2 2], 'xlim', [-200
900], 'yscale', 'log', 'ytick', logspace(log10(minF), log10(maxF), 6), 'ytickl
abel', round(logspace(log10(minF), log10(maxF), 6)*10)/10)
colorbar
title('Self-Expressing (POz)')
subplot(312)
contourf(plotTime, frex, PzAll(:, ptimes(1):ptimes(2), 2), 40, 'linecolor', 'n
one')

```

```

set(gca,'clim',[-2 2],'xlim',[-200
900],'yscale','log','ytick',logspace(log10(minF),log10(maxF),6),'ytickl
abel',round(logspace(log10(minF),log10(maxF),6)*10)/10)
colorbar
title('No Communication (POz)')
subplot(313)
contourf(plotTime,frex,PzAll(:,ptimes(1):ptimes(2)),3),40,'linecolor','n
one')
set(gca,'clim',[-2 2],'xlim',[-200
900],'yscale','log','ytick',logspace(log10(minF),log10(maxF),6),'ytickl
abel',round(logspace(log10(minF),log10(maxF),6)*10)/10)
colorbar

figure(4) % all communication conditions spectrogram for POz
contourf(plotTime,frex,PzAll(:,ptimes(1):ptimes(2))),40,'linecolor','non
e')
set(gca,'clim',[-2 2],'xlim',[-200
900],'yscale','log','ytick',logspace(log10(minF),log10(maxF),6),'ytickl
abel',round(logspace(log10(minF),log10(maxF),6)*10)/10)
colorbar
title('All Communication Conditions (POz)')

```