MIS Quarterly

RESEARCH NOTE

FAKE NEWS ON SOCIAL MEDIA: PEOPLE BELIEVE WHAT THEY WANT TO BELIEVE WHEN IT MAKES NO SENSE AT ALL

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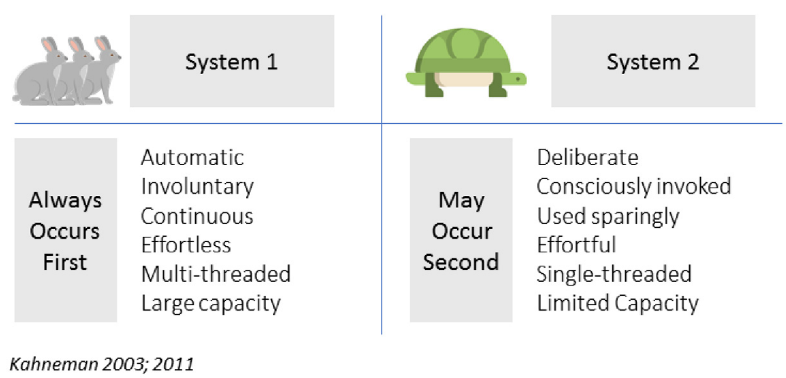


Figure 1. Summary of System 1 and System 2 Processing

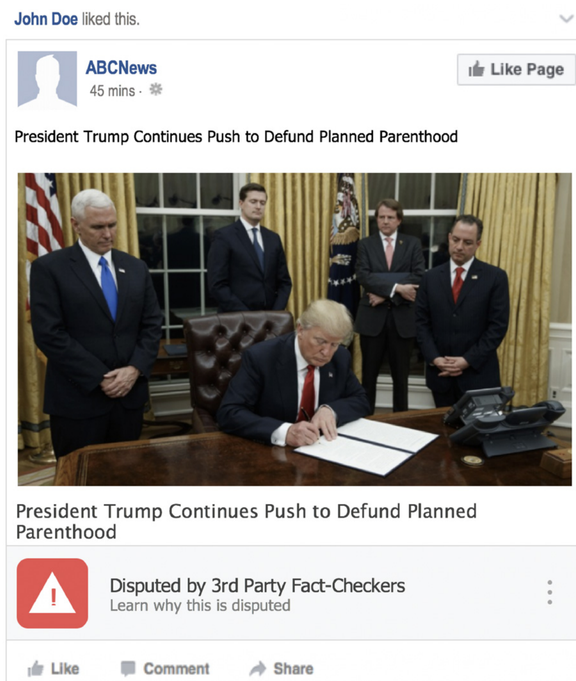


Figure 2. Fake News Flag on a Facebook Headline

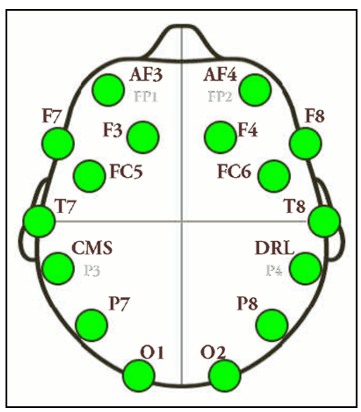
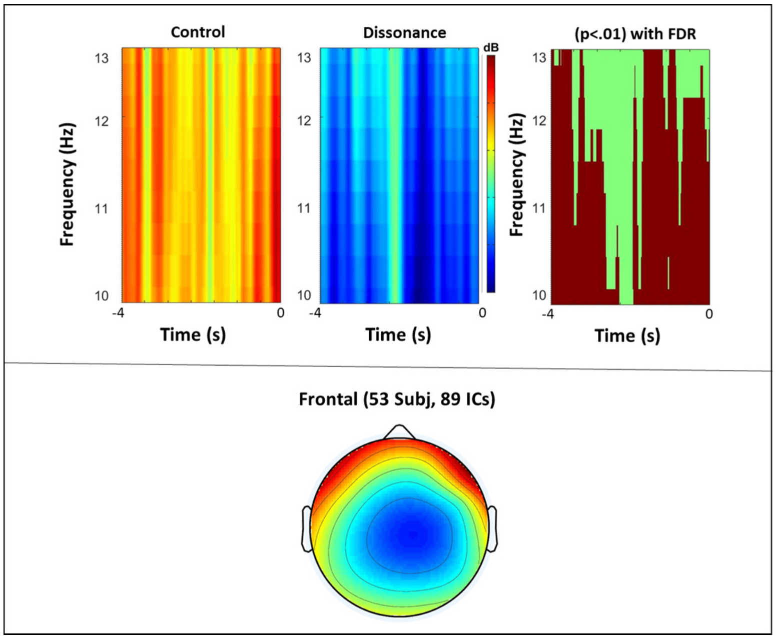
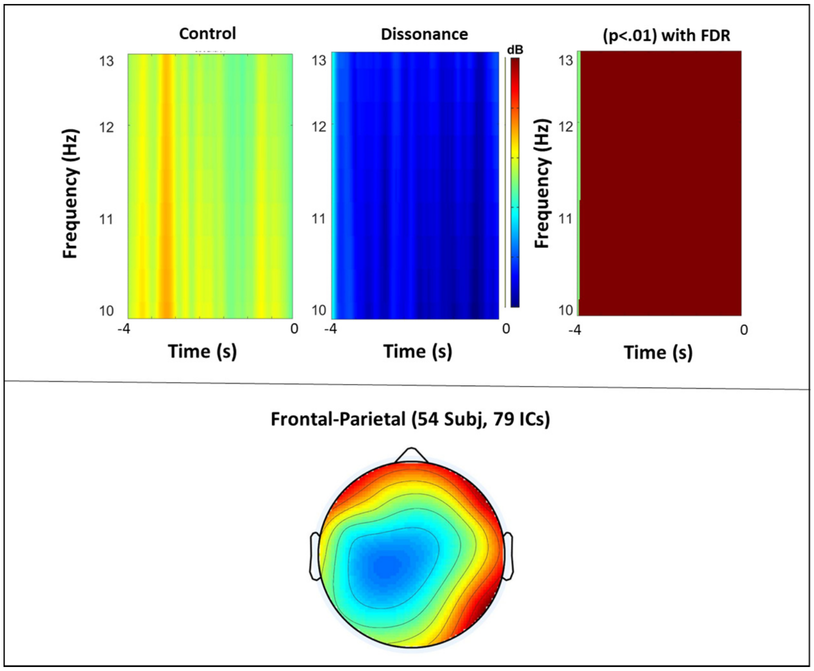


Figure 3. Position of the Electrodes on the EEG Headset with Labels Along the 10–20 System



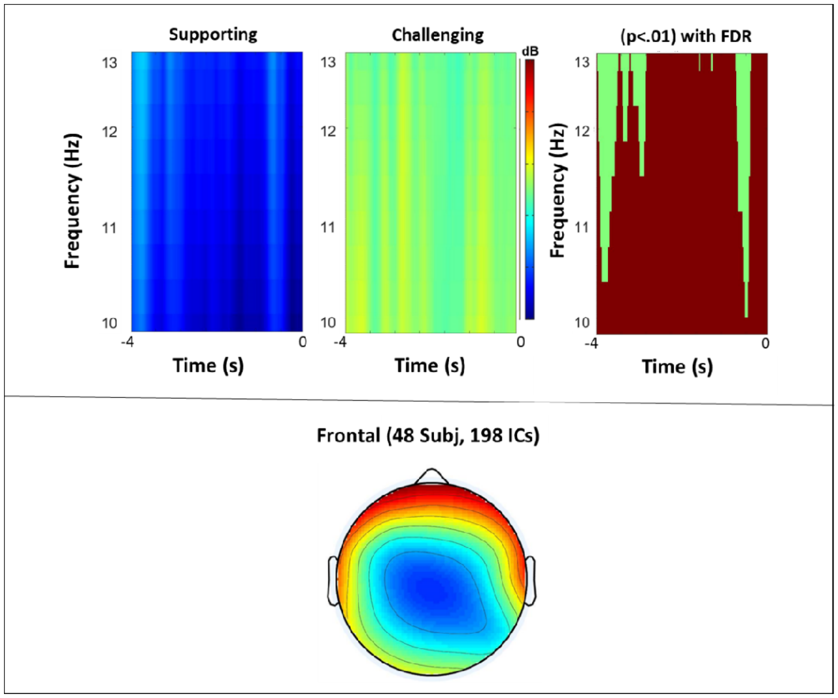
The top left and middle panels show alpha activation for headlines we theorize cognitive dissonance (ones that supported the participant's beliefs and were flagged as false (middle panel) versus all other headlines (left panel); cooler colors (i.e., blue) indicate greater cognition (i.e., greater event-related desynchronization). The right panel shows significant differences (in red) between the two panels, at p = 0..01 with a false discovery rate correction for multiple comparisons. In the scalp map, red regions in left and right frontal cortex] indicates the regions identified as being active (i.e., contributing the most variance) in the cluster.

Figure 4. Differences in Frontal Cortices Cluster Due to Cognitive Dissonance

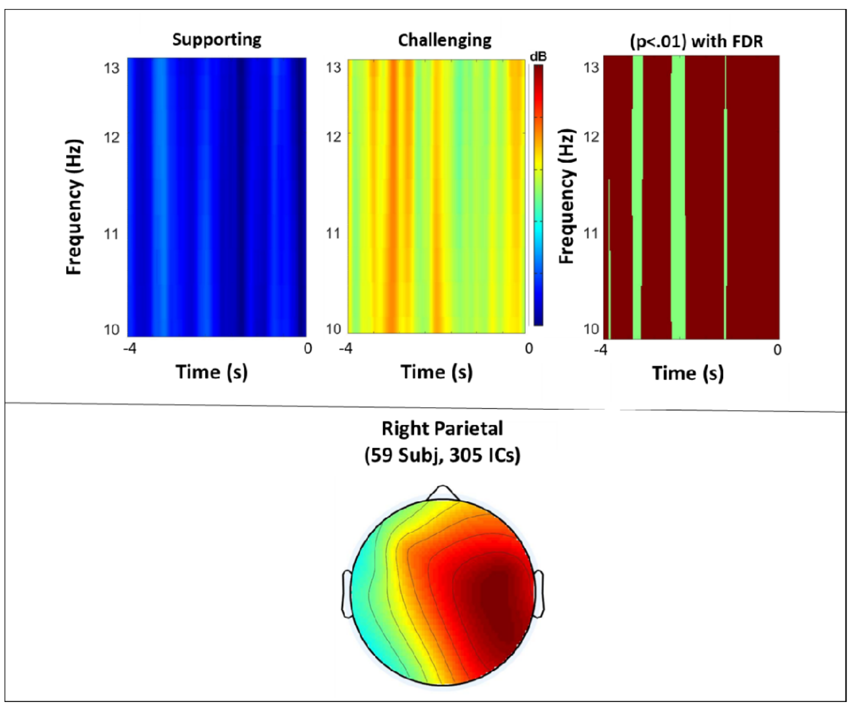


This analysis shows cognition for headlines that supported a participant's political beliefs and were flagged as false (middle panel) versus all other headlines (left panel); blue indicates greater desynchronization. The right panel shows significant differences (in red) between the two panels, at p = 0..01 with a false discovery rate correction.

Figure 5. Differences in Frontal and Right Parietal Cluster Due to Cognitive Dissonance



(a) Frontal Cortices



(b) Right Parietal and Somatosensory

Headlines supporting the participant's beliefs trigger greater cognitive activity in the frontal cortices (Panel a) and in the right parietal and somatosensory regions (Panel b).

Figure 6. Differences Due to Confirmation Bias

Appendix A

Experiment Design

Table A1. Headlines Used in Experiment

Topic	Headline	T/F
Repealing Obamacare/ACA	Contraception No Longer Covered Under National Healthcare Plan	F
	Most Doctors Don't Want the Affordable Care Act Repealed	T
	ACA to be Replaced With Plan That Does Not Cover Pre-Existing Conditions	F
	A Repeal of Obamacare Could Cause Hospitals Major Financial Headaches	T
Student Loans	Pell Grants Discontinued to Provide More Money to Build Wall	F
	Navient, Nation's Largest Student Loan Provider Supplied Incorrect Information	T
	Senators Pushing to Eliminate Student Loan Debt for Victims of Terrorism	F
	President Trump Looking at Changing Federal Student Loan Financing	T
Changes to environmental law	Animal Migration Doors to be Installed in Border Wall to Appease EPA	F
	Judges, Not President Trump, Have Last Decision on Overturning Obama's Environmental Legacy	T
	United States Suing Volkswagen Over Cheating on Environmental Rules	F
	Nominee to Lead EPA Testifies He'll Enforce Environmental Laws	T
Defunding of Planned Parenthood	President Trump Continues Push to Defund Planned Parenthood	F
	Republicans Support Defunding Planned Parenthood Since it Does Not Offer Prenatal Care	T
	Republicans Fund National Pregnancy Care Center That Does Not Provide Contraception	F
	Planned Parenthood Continues to Provide Reproductive Health Services While Tensions Rise	T
Legalization of marijuana	Expect Nationwide Legalization of Marijuana Under Trump Administration	F
	Hawaii Lawmakers Pass Marijuana Legalization Bill Through First Phase of Acceptance	T
	Review Finds that Habitual Smoking of Weed is More Dangerous Than Alcohol	F
	Marijuana Found to Reduce Muscle Pain and Prevent Chemo Nausea	T
Trump's inauguration	Recent Stats Show Record Breaking Population of White Males at Inauguration	F
	Trump Still Claims To Have Largest Inauguration Crowd Ever	T
	Russian Spies Present at Trump's Inauguration - Seated on Inauguration Platform	F
	US Press Secretary Told 4 Untruths in 5 Minutes of Remarks to Reporters	T
Gun law changes	Gun Law Registry Required Based on Race	F
	Lawmakers Consider Changing Law Allowing Concealed Carry on College Campuses	T
	Trump to Enable Concealed Carry Nationwide	F
	Bill to Enable Concealed Carry For Employees in School Districts	T
Abortion	Trump to Sign Anti-Abortion Bill Before End of His First Term	F
	Trump Bans US Funding For Groups That Promote Abortion Overseas	T
	Law to Require All Doctors to Conduct Ultrasound and "Describe Image of Fetus Before Abortion"	F
	Senate and House Passed Bill to Prevent Federal Funds Being Used in Abortion and Abortion Insurance	T
Raising minimum wage	Nationwide Minimum Wage Set to Hit $15 per Hour in 2022	F
	The Federal Minimum Wage Has Lost About 9.6% of its Purchasing Power to Inflation	T
	50% of Small Businesses in Raised Minimum Wage States Set to File Bankruptcy	F
	Minimum Wage Should be $21.72 if it Kept Pace with Inflation	T

Table A1. Headlines Used in Experiment (Continued)

Topic	Headline	T/F
Engagement in international affairs	ISIS Leader Calls for American Muslims to Support Women's March	F
	Increased Concern for US International Trade as Relations among Emerging Nations Grow	T
	China to Discontinue all Trade with the United States	F
	United States Eying India as Key Ally in Coming Years	T
Control	More Celebrities Oppose Trump	T
	Mike Pence Encourages Right to Life Campaigners	T
	Trump Signs New Executive Order on Immigration	T
	Trump Plans Cuts to Environmental Protection Agency	T
	White House Announces Tough Stance in Trade Decisions	T
	Mike Pence Influenced by his Christian Upbringing	T
	Trump Won't Like Newest Poll Showing Approval Ratings	T
	Trump Launches Twitter Tirade Against Alec Baldwin	T
	Disillusioned Democrats Turn to Obama for Guidance	T
	Obama has Big Retirement Plans - And it's Not Golf	T

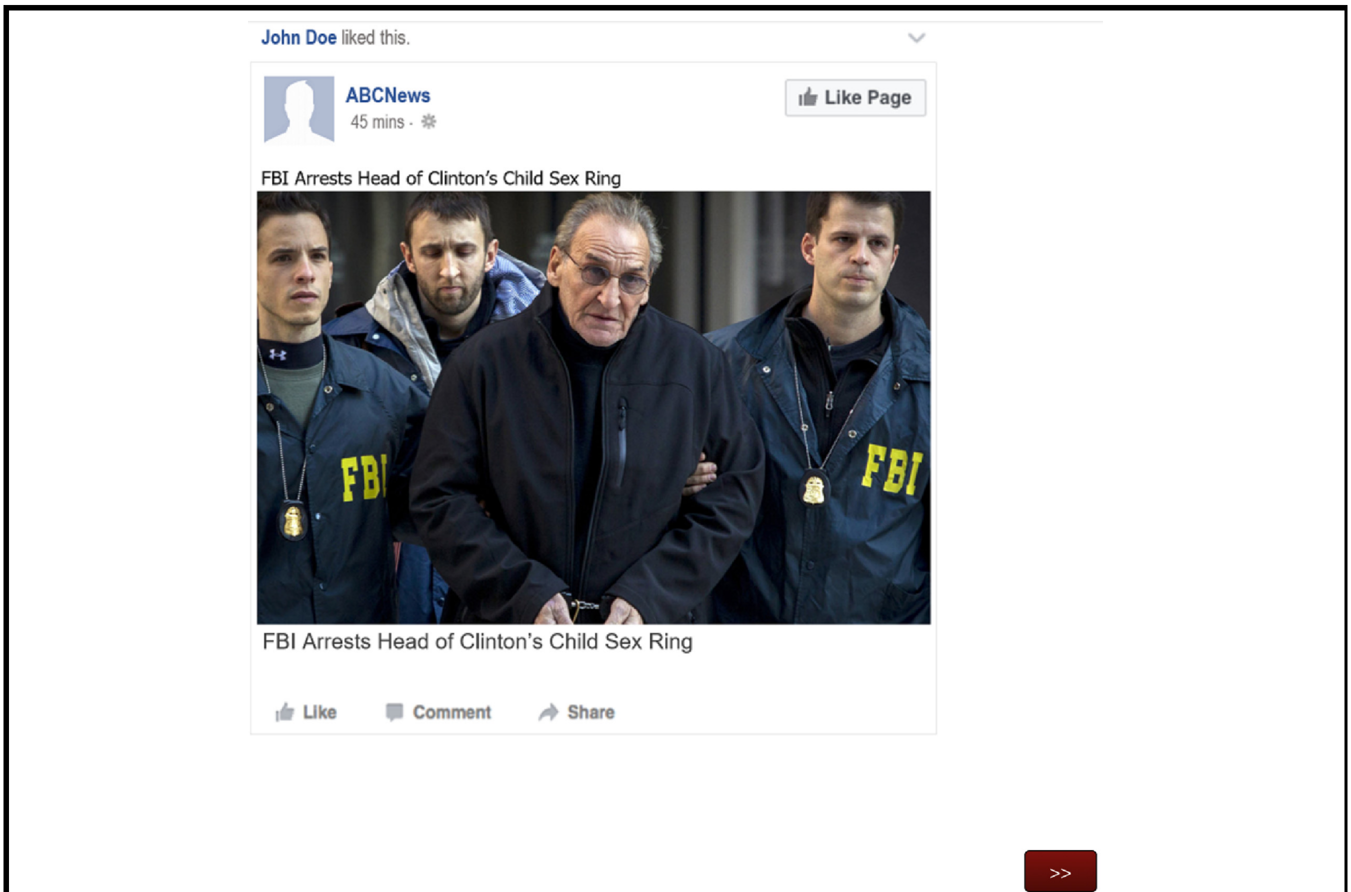


Figure A1. Alternate Image of Stimulus, as Shown to Participants

Appendix B

Measurement Items

Table B1. Descriptive Statistics for Political Affiliation (Conservatism) Items and Variables

Factor	Mean	Std. Dev
Democrat	0.5301	0.4991
Vote for Trump	0.3132	0.4639
I1 Abortion	3.7229	1.7028
I2 Welfare Benefits (reverse)	4.5181	1.5000
I3 Limited Government	4.5783	1.3455
I4 Religion	4.7952	1.5890
I5 Gun Ownership	3.9147	1.7918
I6 Traditional Marriage	4.2410	1.6619
I7 Traditional Values	4.3253	1.4899
I8 Fiscal Responsibility	5.5783	1.1733

Table B.2 Correlations of Political Beliefs (Conservatism) Items and Variables

Factor	Dem	Trump	I1	I2	I3	I4	I5	I6	I7
Democrat	1								
Vote for Trump	-0.613*	1							
I1 Abortion	-0.465*	0.278*	1						
I2 Welfare Benefits (Reverse)	0.567*	-0.458*	-0.548*	1					
I3 Limited Government	-0.367*	0.385*	0.002	-0.280*	1				
I4 Religion	-0.228*	0.251*	0.251*	-0.244*	-0.052*	1			
I5 Gun Ownership	-0.502*	0.554*	0.451*	-0.504*	0.300*	0.091*	1		
I6 Traditional Marriage	-0.227*	0.371*	0.203*	-0.244*	0.169*	0.452*	0.286*	1	
I7 Traditional Values	-0.362*	0.498*	0.378*	-0.388*	0.243*	0.446*	0.421*	0.805*	1
I8 Fiscal Responsibility	-0.338*	0.376*	0.213*	-0.417*	0.376*	0.109*	0.470*	0.200*	0.368*

Appendix C

EEG Analysis

The primary neurophysiological measure in this study was electroencephalography (EEG), with a focus on the alpha band frequency. EEG measures were collected using an Emotiv EPOC, which is a 14-channel system. The electrodes dispersed over the scalp along the 10-20 system (Herwig et al. 2003). The system sampled at 128 Hz, a basic finite impulse response (FIR) high-pass filter of 1 Hz was applied to the data. No additional amplifiers are needed with Emotiv EPOC system. The reference electrodes were located at P3 and P4. Each trial consisted of 0 to 4 seconds *at the end* of the online article image viewing. This was done to capture the alpha frequencies present after the participant had time to process the online article headline. Following the data recording, the EEG data was visually inspected for eye movements and muscle artifacts, which were rejected from the data channels. In addition, the analysis in EEGLab provides an artifact rejection by probability, which was employed to detect artifacts greater than five standard deviations from the mean.

There has been debate within the cognitive neuroscience community about the validity of low-cost, consumer grade EEG systems. The Emotiv system is a low-density electrode EEG device that collects a veracious signal of underlying cortical activity, and has been used in prior studies published in leading business journals (Minas et al. 2014). Many studies have scrutinized the Emotiv device in a variety of settings such as, examining working memory (Wang et al. 2016), auditory ERPs (Badcock et al. 2013), mobile brain-computer interfaces (Debener et al. 2012), reliable detection of the P-300 wave and other ERPs (Ramírez-Cortes et al. 2010; Wang et al. 2016), human–computer interaction research (Taylor and Schmidt 2012), hemispheric asymmetry (Friedman et al. 2015), among others. These studies have found Emotiv to obtain a reliable and valid signal of underlying cortical activity and has been shown to be as good as larger high-density systems.

One valid concern raised about the Emotiv system is that some users observed lost data packets due to its use of wireless communication. This study has considered this concern in three ways. First, the Emotiv data file contains an "interpolated" marker that indicates if a packet was successfully transmitted ("0") or if it was interpolated ("1"). We did not observe any missed data packets in our data. Second, during our analysis, we visually inspected all trials when filtering for artifacts (e.g., ocular artifact). Dropped data packets would have been caught during this phase of the analysis. Finally, the dropped data packets would be random in nature, so there would not be any systematic bias in the data.

As a neurophysiological technique, EEG is the measurement of the electrical signals present at the surface of the scalp. An EEG system is capable of measuring the relatively small electrical signals produced in the superficial areas of the underlying cortices. EEG is widely regarded as having the highest temporal resolution of all the neuroimaging techniques, capable of accurately measuring electrical signals on the order of milliseconds. Over time, these electrical signals form complex wave patterns or oscillations. Different oscillations have been shown to be related to cognition. For example, the alpha wave, an oscillation with a frequency of 8–13 Hz, has been shown to be closely related to attention, with alpha wave desynchronization corresponding to higher levels of attention (Kelly et al. 2006; Klimesch 2012; Makeig et al. 2002). Many studies have shown that alpha waves vary by task. For example, alpha waves over the left frontal cortex are related to cognitive load, working memory, and attention, while alpha waves over the occipital lobe are related to visual attention (Başar et al. 2001).

The EEG device consists of electrodes, which connect with the scalp surface via felt pads saturated with saline solution. Generally, EEG devices measure electrical activity in relation to the deviance from another pair of sensors on the scalp. For the Emotiv device, the reference electrodes are located at P3 and P4 over the inferior, posterior parietal lobule (Herwig et al. 2003). All other channels will be measured in relation to the electrical activity present at these locations, sampled at 128 Hz. Impedances were verified and data were collected using Emotiv TestBench Software Version 1.5.0.3, which can export data into comma-delimited format for subsequent analysis in MATLAB, a numerical computing environment developed by MathWorks. Analyses were performed in EEGLab, a toolbox for MATLAB (Delorme and Makeig 2004).

Data Cleaning and Preparation

Continuous EEG data were cleaned and analyzed using EEGLab Version 14.1.1. 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 (Delorme and Makeig 2004).

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. One participant had a channel with poor impedance that was removed from the analysis. No subject had more than one channel rejected.

ICA Analysis of EEG Data

After the trials that contained artifacts (i.e., large voltage variation across a channel), the continuous data was submitted for an independent components analysis (ICA). Presenting continuous data for ICA analysis allows for a baseline of neurophysiological data over the recording period prior to extracting the event-related data (Pizzagalli 2007). A common problem in neuroimaging research results from the collection of large amounts of data which, based upon 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 non-active at others (i.e., activity is not normally distributed across the scalp) (Onton et al. 2005). 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 (Onton and Makeig 2006). 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 dataset, as the algorithm is working in an N-dimensional space (where N is the number of electrodes). After the ICA was completed on the individual data, the trials were extracted into epochs (or time windows of the last 4 seconds the participants viewed the data).

Finally, using the K-means component of EEGLab the independent components at the individual level were grouped into clusters containing similar components using procedures recommended by Delorme and Makeig (2004). This procedure clusters similar ICs based upon their latency, frequency, amplitude, and scalp distribution (Onton et al. 2005). Eight clusters were generated and evaluated for the final analysis.

Event-Related Spectral Perturbation (ERSP) Analysis

EEG is a neurophysiological measurement of post-synaptic electrical potentials on the surface of the scalp on the order of milliseconds (Gibbs and Gibbs 1941). Electrodes are placed in specific locations on the scalp and collect the summation of synchronized activity from underlying pyramidal neurons lying near the surface of cortex. The measure at each electrode location is then compared to either a reference electrode located elsewhere on the scalp or by using a common average reference (CAR) in place of a reference electrode (Harmon-Jones and Peterson 2009). 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), theta (4–8 Hz), alpha (in this study broken into lower alpha 8–10 Hz and upper alpha 10–13 Hz), beta (13–20 Hz), and gamma (>20) (Harmon-Jones and Peterson 2009). Time-frequency analysis enables the examination of changes in wavelet oscillations over time within a frequency band of interest (Makeig 1993) and has been cited as a promising technique for research (Srinivasan 2007).

We used event-related spectral perturbation (ERSP) for its ability to model both time and frequency changes occurring in the independent components (ICs) over the time window specified and because it is especially appropriate for low-density EEG systems. The ERSP shows mean changes in log power from some pre-specified baseline mean value (Makeig 1993). We generated ERSPs that were at the last 4 second of the viewing period for the online article.

Two analyses were completed. The first analyzed the ERSPs generated when headlines supported or challenged a participant's thinking. A second set of ERSPs were generated by participants coded by the support and flag interaction (i.e., dissonance condition) at the individual participant, question-level. Scalp maps provide information as to the dispersion of activity within a frequency band across the scalp. We set the statistical threshold at ($p < .01$) and corrected for multiple comparisons using the false discovery rate (FDR) of Benjamini and Hochberg (1995) to minimize Type I error with only a marginal loss of statistical power.

Appendix D

Our Context-Specific Theorizing

We used the work of Hong et al. 2014 (especially their Table 1) to help us contextualize our theoretical arguments in the specific domain of interest (i.e., social media and fake news; see Table D1).

Guideline 1. The first guideline is to ground the research in general theory. It is important to note that we are *not* testing a general theory (and nor do Hong, et al. advocate for this). Instead, the focus is on the phenomenon (belief in fake news on social media) and understanding what general theory could be used to explain behavior in this context. This is a subtle but important difference; research testing a general theory would start with the theory and search for a context in which to test it, whereas our research starts with a technology use phenomenon and searches for a general theory that could be used to ground theorizing about it. Hong et al. imply that a general theory might suffice, but often provide examples with several general theories. In our experience, grounding of an IS phenomenon usually requires several general theories because the phenomenon occurs at the intersection of prior research.

In our context, belief in fake news on social media, we identified three general theories that would serve as good general theories to ground our theorizing: dual process cognition (System 1/2), confirmation bias, and cognitive dissonance.

Guideline 2. The second guideline is contextualizing the general theories. That is, selecting the relevant constructs from the general theories and omitting the irrelevant constructs. In other words, we seldom choose to use the entire general theory; using general theory in entirety is more likely when the research goal is to test a general theory, rather than understanding a technology use phenomenon. By judicious selection of constructs, we are able to get a more parsimonious and focused theory that explains technology use in the selected context.

In our context, we focused only on the belief of new information. System 1/2 theories also include constructs on how knowledge structures are built, which we omitted. We omitted all parts of the theories that explained knowledge construction and focused only on the parts that pertained to our context: the processing of new information. System 1/2 theories include several constructs that often trigger humans to invoke System 2 cognition (e.g., being startled; strong aversive stimuli (e.g., vomit)); we included only FOR as it was most appropriate for our context of social media.

Guideline 3. The third guideline is the identification of context-specific factors. This first involves identifying core constructs in the general theories and seeing how they instantiate in the context of interest. One key aspect of the context is the hedonic mindset of the user. The user is not striving to figure out what is true and fake but rather is passively seeking enjoyment. Thus, users have little motivation to invoke System 2 cognition. This means that users will be unlikely to invoke System 2 cognition unless something pushes them hard to use it.

The second aspect of this guideline is examining research with other relevant technologies and/or an in-depth analysis of the target technology. In other words, identifying what is similar and different about this context from other technology use contexts that might be related. A related technology use context is reading reviews on e-commerce sites while shopping for a product. Users who are reading ecommerce reviews are in a utilitarian mindset and have a goal to select the right product; users do not read products reviews purely for entertainment. This again reinforces the contextual factors that social media users will have less motivation to invoke System 2 cognition than when they are shopping for a product, making it hard to generalize from research on e-commerce to this context. There are fake reviews on e-commerce sites, but there are usually more true reviews than fake; on social media there is more fake news than true news, which again makes it hard to generalize from e-commerce research.

Another related technology use context is reading news stories at news web sites (e.g., CNN, Washington Post, National Enquirer). In this case, the user has chosen to read news and has chosen the news source, usually with some understanding of the likely truth of the stories. In the social media context, the platform's algorithm chooses what the user will see next, whether it is a post from a friend, content from a news provider, or a paid advertisement masquerading as a news story. Thus, on social media, the user often has little awareness of the source of the news story, and because there is more fake news than true news, the odds are the news story is fake. Once again, this suggests we cannot generalize from the news reading technology use context to the social media context.

These analyses produced three context-specific factors (the hedonic mindset; the source of information; and the volume of fake news) that influenced how we instantiated core constructs from the three general theories in this context and how we considered but ultimately did not generalize research from other technology use contexts.

Guideline 4. The fourth guideline is modeling context-specific factors. Hong et al., who studied TAM in a library setting, decomposed ease of use into two context-related sub-factors (screen layout and terminology) and measured their impact on usage intentions, versus the more general ease of use construct in the general TAM theory. In our case, we used the alignment of the headline with the participant's political beliefs as a measure of confirmation bias. We used the placement of the fake news flag on a headline aligned with the participant's beliefs as a test of cognitive dissonance; that is would the flag create cognitive dissonance?

Guideline 5. The fifth guideline is examining the interplay of the technology artifact and the other factors. Our research focused on the technology artifact of the fake news flag. We examined how the fake news flag affected cognition and beliefs in the presence of a headline that aligned with the user's beliefs. In other words, did it create cognitive dissonance and was it strong enough to overcome confirmation bias?

Guideline 6. The sixth guideline pertains to research investigating mediation and moderation, which does not apply to our study.

Table D1. Application of Guidelines for Context-Specific Theorizing in IS Research (Adapted from Table 1 in Hong et al. 2014)

Hong et al. 2014 Guidelines	Summary of Hong et al. 2014 Description	Our Implementation
1. Grounded in general theory	Context-specific research could be built on a general theory that is applicable to the research domain of interest. For example, the theory of reasoned action and the theory of planned behavior are used to ground the technology acceptance model.	We identified three general theories: dual process cognition (System 1/2), confirmation bias, and cognitive dissonance.
2. Contextualizing and refining the general theories	The general theories need to be contextualized to the specific research domain by selecting relevant constructs and omitting irrelevant constructs.	Our context was the processing of new information in social media, so we omitted all parts of the theories that were not relevant.
3. Thorough evaluation of the context to identify context-specific factors	Context-specific factors could be identified by linking core constructs in the general theories to the context. Context-specific factors could also be identified from past research on relevant technologies and/or an in-depth analysis of the technology under investigation.	These analyses produced three context-specific factors: the hedonic mindset; the source of information; and the volume of fake news.
4. Modeling context-specific factors	The core constructs in the general theory can be decomposed into context-specific factors that are then tested. For example, a context specific factor of screen layout could be modeled as a direct predictor of usage intention rather than the more general ease of use construct.	We used the alignment of the headline with the participant's political beliefs as a measure of confirmation bias. We used the placement of the fake news flag on a headline aligned with the participant's beliefs as a test of cognitive dissonance.
5. Examination of the interplay between the IT artifact and other factors	Interactions among context-specific factors pertaining to the specific technology, user, and usage context should be examined. For example, the interactions between computer self-efficacy and context-specific ease-of-use factors (e.g., screen layout).	Our research focused on the technology artifact of the fake news flag and how it affected cognition and beliefs in the presence of a headline that aligned with the user's beliefs.
6. Examination of alternative context-specific models	When the objective is to examine the indirect influence of context-specific factors, alternative context-specific models could be formulated based on the selected general theory. Models of mediation, mediated moderation or moderated mediation that involve the context-specific factors and the relevant core constructs could be examined.	This is not applicable to our study as we are not interested in mediation or moderation.

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