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RESEARCH NOTE

FAKE NEWS ON SOCIAL MEDIA: PEOPLE BELIEVE WHAT THEY WANT TO BELIEVE WHEN IT MAKES NO SENSE AT ALL[1]

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Fake news (i.e., misinformation) on social media has sharply increased in the past few years. We conducted a behavioral experiment with EEG data from 83 social media users to understand whether they could detect fake news on social media, and whether the presence of a fake news flag affected their cognition and judgment. We found that the presence of a fake news flag triggered increased cognitive activity and users spent more time considering the headline. However, the flag had no effect on judgments about truth; flagging headlines as false did not influence users' beliefs. A post hoc analysis shows that confirmation bias is pervasive, with users more likely to believe news headlines that align with their political opinions. Headlines that challenge their opinions receive little cognitive attention (i.e., they are ignored) and users are less likely to believe them.

Keywords: Cognition, social media, information quality, fake news, fact-checking, confirmation bias, cognitive dissonance, EEG, NeuroIS

> There is today a special need for propaganda analysis. America is beset by a confusion of conflicting propagandas, a Babel of voices, warnings-charges, counter-charges, assertions, and contradictions assailing us continually through press, radio and newsreel (Institute for Propaganda Analysis 1938, p. 1).

> We are facing nothing less than a crisis in our democracy—based on the systematic manipulation of data to support the relentless targeting of citizens, without their consent, by campaigns of disinformation and messages of hate (House of Commons 2018).

Introduction

In the early days of the Internet, people argued it would enable greater transparency of information, which would increase the quality of democracies (Abramson et al. 1990; Tewksbury 2003). It was argued that information from

[1] Gerald Kane was the accepting senior editor for this paper. Ryan Wright served as the associate editor.

The appendices for this paper are located in the "Online Supplements" section of *MIS Quarterly*'s website (https://misq.org).

various sources would enable people to find their own information, and this decreased reliance on traditional news sources would improve democracy.[2] This vision has been realized with the rise of nontraditional news on social media, but some might argue that this has harmed democracy, rather than improved it. An editorial in *Science* calls on the scientific community to help reporters and the general public better identify and avoid fake news (Weiss 2017).

Social media has become a common source for news; more than 50% of American adults read news on social media (Gottfried and Shearer 2016). Social media is different from other media providing news (e.g., TV news, news websites, and mobile phone news apps) because users do not choose the source of all of the articles they see on social media. Instead, proprietary algorithms provide targeted information with little transparency. With other news media, users pick the source first, and do so with a familiarity of the nature of the source (Rice et al. 2018).

With social media such as Facebook, articles from a wide variety of sources appear on users' newsfeeds. News articles are intermixed with sponsored articles (i.e., paid advertisements) and posts from family and friends. All of these may be intentionally or unintentionally true or false, but some are explicitly designed to influence (Shane 2017). For example, Cambridge Analytica developed tools to influence users (Granville 2018). About 23% of social media users report that they have accidently *or intentionally* shared fake news (Barthel et al. 2016). Over 60% say that fake news leaves them confused about what to believe (Barthel et al. 2016), and research suggests that fake news spreads faster than true news (Vosoughi et al. 2018).

Social media has moved quality control for detecting fake news from trained journalists to regular users (Kim and Dennis 2019). About 84% of Americans believe that they can detect fake news (Barthel et al. 2016), but how do users detect fake news when most have no direct knowledge of the facts (i.e., they have not witnessed the events)?

In this study, we examine the effect of a Facebook "fake news" flag and how social media users respond to it. Simply put, we examine the question: Are fake news flags effective in altering users' beliefs? We use electroencephalography (EEG) to examine cognitive processes (Dimoka et al. 2012; Vance et al. 2018). We found that flagging articles as fake triggered more cognitive activity, but it did not change users' beliefs in them. We further found that articles that aligned with the user's *a priori* opinions triggered increased cognitive activity, with users more likely to believe them; articles that challenged users' opinions were less thoroughly considered and were less likely to be believed. Our findings triangulate around one explanation: confirmation bias—users believe what matches their prior opinions, undeterred by the actual truth of an article or a fake news flag. As John Mellencamp said in his 2004 song, *Walk Tall*, "People believe what they want to believe/when it makes no sense at all" (Mellencamp 2004).

Prior Theory and Research

Fake news is not a new phenomenon (McGrath 1986), but the problem is getting worse (Schulze 2018). The speed with which information can be disseminated on social media creates an opportunity to rapidly spread fake information. To combat this issue, several fact-checking initiatives have been started (Graves 2016; Lowrey 2017). Some rely on human raters, while others rely on automated tools. The question is: Is fact-checking effective in stopping fake news? In the sections below, we examine why assessing the truthfulness of news on social media is difficult, and how fake flags and confirmation bias influence users' beliefs. We focus on Facebook; it has over 2 billion active users and is a popular source for news (Gottfried and Shearer 2016; Statista 2018).

Assessing the Truthfulness of News on Social Media

Context matters (Johns 2006, 2017). "One way to develop richer theories that provide actionable advice is to take the context into greater consideration" (Hong et al. 2014, p. 2). Much past IS research has examined work contexts, but our focus is on social media. Most individuals use social media for hedonic purposes (Chauhan and Pillai 2013), such as connecting with friends, rather than utilitarian purposes (Johnson and Kaye 2015). Following steps 1 through 4 in Table 1 of Hong et al. (see Appendix D), we ground our research in two general theories (confirmation bias and cognitive dissonance) and examine how they influence behavior in this use context. We identified three context-specific factors that make consuming news on social media different from other contexts in which users view information on the Internet.

First, the user's mindset is different, which affects how information is processed. The consumption of news on social media is different from the consumption of information elsewhere on the Internet. For example, it is well known that some product reviews are fake (Dwoskin and Shaban 2018; Dwoskin and Timberg 2018; Roberts 2013). A key difference

[2]Democracy is defined as "the belief in freedom and equality between people, or a system of government based on this belief" (Cambridge Dictionary 2018).

between fake reviews and fake news is that users do not read product reviews for entertainment; they read reviews for information to make a decision, knowing there is a monetary incentive to make the best, most well-informed decision. Thus, users reading fake reviews are in a utilitarian mindset; their goal is to understand the meaning of the information in the review and to decide which reviews should be considered in making a decision. Minas et al (2014) examined a utilitarian mindset in virtual team interactions in a decision-making context. The study found confirmation bias was present while individuals processed information in a decision-making team-based chat. In contrast, the hedonic mindset when reading social media news means the user's goal is *not* to determine what is true and fake; instead the goal is enjoyment and pleasure. The user will avoid effortful activities that feel like work (e.g., thoughtful information processing) and activities that do not bring enjoyment (e.g., reading stories that your favorite sports team lost). Users engage with articles that make them feel good, which tend to be articles supporting their beliefs.

Second, the source of the information is not clear. With Internet news and traditional news media, we visit the web site of our favorite news network or open our local newspaper; we pick the source before we read articles and do so with some understanding of the source's framing or limitations (Rice et al. 2018). Facebook is different because users do not choose the source of the articles; instead, Facebook's algorithms choose the articles. Although some users subscribe to certain sources by following them on social media, many other sources arrive on our newsfeeds from advertisements, sharing by friends, and algorithmic decisions. Articles from many different sources—some reputable, some disreputable—are intermixed. A fake news article may be presented between a CNN article and Aunt Martha's cookies. The source of the story is obscured and users in a hedonic mindset are not motivated to invest effort to find and understand the source (Kim and Dennis 2019).

Finally, the sheer volume of fake news makes it challenging to separate truth from fiction. More fake news articles are shared on social media than real news (Silverman 2016). Many fake news sites have appeared on Facebook with the express purpose of spreading carefully crafted propaganda or to discredit a specific person (BBC 2017). Their low cost and ubiquity is one reason that fake news is common on social media (Barthel et al. 2016).

These three contextual factors—a hedonic mindset, a lack of cognizance of the source, and the volume of fake news—combine to create a context in which social media users do not think as critically as they should when presented with news on social media. More than half the articles shared on Twitter are shared *without* the user reading them, let alone thinking critically about them (Gabielkov et al. 2016). Nonetheless, research shows that there is a bias toward taking an opinion on contentious social media topics, rather than remaining neutral (Jonas et al. 2001). This is true even when users lack information on the topic—or bother to read an article—which helps the spread of fake news (Jonas et al. 2001).

Fact-Checking Fake News

In response to the rise of fake news, fact-checking services have become more common. Many solutions have been developed to automate fact-checking. *Truthy* (Ratkiewicz et al. 2011) and *Hoaxy* (Shao et al. 2016) are two such solutions, which can provide relatively quick results for news articles. *Truthy* fact-checks sites that are well-known for verifying the truth of news articles, such as Snopes.com, politifact.com, and factcheck.org, as well as checking known disreputable sites for fake news articles. Fact-checking can influence credibility, especially if done by independent fact-checkers (Wintersieck 2017).

Facebook incorporated fact-checking into its platform and began flagging fake news articles in late 2016 by appending a statement that an article was "disputed by 3rd party fact-checkers" when fact-checkers determined an article was fake (Isaac 2016). Thus, fact-checking was integrated into the presentation of the article; users did not need to invest effort to seek out a third-party fact-checking site. Facebook discontinued the flag in late 2017 (Meixler 2017). One might conclude that Facebook's actions indicate that fact-checking fake news is not effective. However, the undisclosed reasons why a for-profit corporation makes decisions—especially when its goals are unclear—are not theoretically compelling.

After Facebook discontinued its fake news flag, third parties began offering their own fake news flagging services that can be integrated into Facebook. For example, NewsGuard provides a browser plugin using source reliability ratings from teams of expert journalists and consultants for more than 4,500 news sites that account for 98% of the online news in the United States (NewsGuard 2018). The plugin automatically displays a fake news flag whenever content from a disreputable source is displayed, whether in Facebook or another web site.

Fact-checking is most important when the user wants to believe a headline; flagging a headline when the user was unlikely to believe it without the flag adds little value. Thus, we focus on the situation where a user is inclined to believe a fake headline, but it is flagged as false.

The Effects of Confirmation Bias

One factor influencing belief is confirmation bias: people prefer information that matches their prior beliefs (Koriat et al. 1980; Minas et al. 2014; Nickerson 1998). Confirmation bias is a bias against information that challenges one's beliefs (Nickerson 1998); it is driven by the fundamental nature of our cognition (Kahneman 2011).

Researchers have long argued that there are two distinctly different cognitive processes, and there are many dual process models of cognition (Evans 2008). Two complementary models emerged in the 1980s. The heuristic–systematic model (HSM) (Chaiken 1980; Chaiken and Eagly 1983) argues that attitudes are formed by the systematic application of considerable cognitive effort to comprehend and evaluate the validity of available information (called the systematic route), or by exerting little cognitive effort using simple heuristics on readily accessible information (called the heuristic route). The elaboration likelihood model (ELM) (Cacioppo et al. 1986; Petty and Cacioppo 1986) argues that attitudes are formed based on deliberate and active consideration of available information to evaluate the true merits of a particular position (called the central route) or as a result of a less cognitively involved assessment of simple positive or negative cues in the context (called the peripheral route).

There are distinctions between HSM and ELM, but they share a common fundamental basis. Both argue that there are two distinct conscious cognitive processes by which attitudes are formed, and that these two processes differ in the amount of cognitive processing expended (e.g., a quantitative difference) and in the cognitive approach used to evaluate information (e.g., a qualitative difference). Both argue that individuals choose which route to invoke based on their ability and motivation to engage in extensive cognition. Both have evolved to argue that the routes are not distinct, so cognition is more of a continuum of processing (Kitchen et al. 2014). ELM is the more popular and is still used today (Cacioppo et al. 2018), although some researchers dispute the notion of dual process models (Melnikoff and Bargh 2018).

Many newer dual process models have been developed (Evans 2008; Evans and Stanovich 2013), because research suggests that many of the fundamental arguments of HSM and ELM (as revised over time in response to criticisms (Kitchen et al. 2014)) are not accurate. For example, the routes are not mutually exclusive (both can be used); the routes are not on a continuum (they are separate); individuals do not choose the route to use (the heuristic route is automatic); individuals cannot avoid the heuristic route (its use is involuntary); and the systematic route cannot operate by itself (the heuristic route always precedes it) (De Neys 2018; Evans 2008; Evans and Stanovich 2013; Kahneman 2011; Pennycook et al. 2018).

In this paper, we adopt the widely accepted dual process model of Stanovich (1999) and Kahneman (2011) who call these separate processes System 1 and System 2—System 1 for the automatic cognition that always occurs first, and System 2 for the deliberate cognition that sometimes occurs second (the names indicate the order in which they are used) (see Figure 1 for a summary). We note that Stanovich has more recently suggested using the terms Type 1 and Type 2 because the use of the word "system" implies there are separate areas in the brain that are dedicated to each type of cognition, which is not the case (Evans and Stanovich 2013).

System 1 runs continuously, and delivers conclusions automatically and involuntarily (Kahneman 2011). Intuition is System 1 at work (Achtziger and Alós-Ferrer 2013; Dennis and Minas 2018). When we receive new information, our System 1 cognition automatically searches long-term memory for confirming evidence and generates a response in less than one second (Bargh and Ferguson 2000; Carlston and Skowronski 1994; Fazio et al. 1986). This process is nonconscious and unavoidable; we cannot prevent it (Evans and Stanovich 2013; Kahneman 2011). It supplies these assessments, even though they are not asked for (Bellini-Leite 2013; Dennis and Minas 2018; Kahneman 2011; Thompson 2013). System 1 is a set of subsystems that run in parallel triggered by different bits of incoming information (Bellini-Leite 2013; Evans 2008, 2014; Thompson 2013). When the different subsystems produce matching results, System 1 produces a "feeling of rightness" (FOR) that says it is confident about its conclusions (Bago and De Neys 2017; De Neys 2014; Thompson et al. 2011). When there is conflict among subsystems' results, FOR creates a sense that something is not right (Bago and De Neys 2017).

In contrast, System 2 cognition is single-threaded (Dennis and Minas 2018) and has much less processing capacity (Evans 2014). System 2 is under our deliberate control, so we can choose to invoke it, but it is easily overwhelmed. System 2 cognition is effortful (Kahneman 2011), and most humans are "cognitive misers" who attempt to minimize cognitive effort (Taylor and Fiske 1978). Thus, we tend to adopt the conclusions of System 1, often without thought (Kahneman 2011). Common triggers causing us to invoke System 2 are a negative stimulus or a surprise (Kahneman 2011), or a FOR that indicates conflicting results (Bago and De Neys 2017).

The net result is confirmation bias (Nickerson 1998). When we see new information, our System 1 automatically, and in less than one second, confirms that it matches our prior knowledge and we are inclined to believe it. Or, our System 1

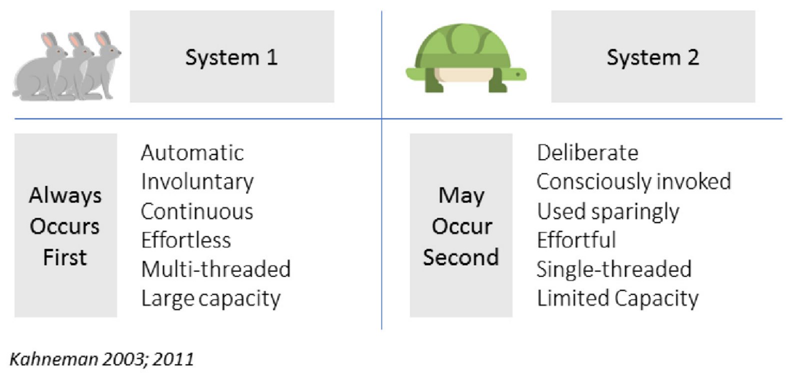


Figure 1. Summary of System 1 and System 2 Processing

tells us that it does not match and we should not believe it (Kahneman 2011). Unless we are motivated to expend cognitive effort and invoke System 2, we simply accept the conclusion of System 1 with little thought (Kahneman 2011). And if we were to invoke System 2, how would it help us determine if a news story was true? Unless we have witnessed the events in a story there is no unambiguous way to determine if the story is true or false. One must conduct extensive research to produce an accurate conclusion. Thus, people are likely to accept their System 1 conclusion and believe information that matches preexisting views (Allcott and Gentzkow 2017).

Confirmation bias also affects the time taken. The conclusion by our System 1 that new information matches our beliefs is produced in less than a second and simply accepting this takes little time. If our System 1 indicates that we should reject the new information, we are inclined to spend only a little longer before discarding it (Haidt 2012; Kahneman 2011). Minas et al. (2014) found that in a utilitarian mindset, all pieces of information are initially, quickly considered (by System 1), but only the information that matched *a priori* beliefs was selected for System 2 processing. Similarly, Turel and Qahri-Saremi (2016) found that System 1 was linked to impulsive and problematic use of social media and System 2 to more rational and controlled use.

Two aspects of the social media context suggest that social media may exacerbate confirmation bias. First, research suggests that individuals in a hedonic mindset may be less likely to critically consider information than those in a utilitarian mindset, as their consumption is tied to what they desire reality to be, rather than what they know to be real (Hirschman and Holbrook 1982). When in a hedonic mindset, we are less likely to expend the cognitive effort to invoke System 2, and more likely to accept the biased conclusions of System 1. Second, social media enables users to choose the news they like and learns their preferences so that it deliberately displays more articles matching their choices. This causes a decreased range of information displayed on a user's newsfeed, so that the news on social media is often biased (*The Wall Street Journal* 2016). Users' realities on Facebook differ based on what they read and who their friends are (*The Wall Street Journal* 2016). There are sharp differences in liberal and conservative newsfeeds, with fake news aligned with political beliefs more likely to be seen and shared by users in "echo chambers" of biased information (Bozdag and van den Hoven 2015; Cerf 2016; Colleoni et al. 2014). This bias inundates users with news—real and fake—that supports their views (Bennett and Iyengar 2008; Knobloch Westerwick and Lavis 2017). Such a stream of biased messages intensifies confirmation bias (Nickerson 1998).

Creating Cognitive Dissonance

One approach to interrupting confirmation bias is to create cognitive dissonance by adding a fake news flag to false stories. Cognitive dissonance occurs when users are presented with two pieces of conflicting information that cannot be readily reconciled (Festinger 1962; Mills 1999). A fake story that users want to believe because it aligns with their *a priori* beliefs combined with a flag that says it is false creates cognitive dissonance. System 1 makes an instant judgement but the conflicting information makes this judgement difficult (Kahneman 2011); the results are unreliable and the FOR tells them something is amiss (Bago and De Neys 2017). This contradiction causes cognitive discomfort (Aronson 1969). The user must decide either to ignore the discomfort or invest effort to resolve it. If the issue is unimportant to them, users ignore the cognitive dissonance and accept what their prior beliefs say (Nickerson 1998). Otherwise, they invest effort by invoking System 2 to decide which piece of conflicting information is true (Aronson 1969; Kahneman 2011), which takes longer and requires greater cognitive activity.

When System 2 goes to work to resolve the dissonance, it is influenced, sometimes very strongly, by the unreliable results of System 1 (Kahneman 2011). The System 1 results are in working memory and become part of the problem space (Thompson 2013). System 2 has equal access to the information and the unreliable result of System 1, and uses both (Thompson 2013). Information is often ambiguous and can be interpreted in different ways (Srull and Wyer 1979). System 2 gives more weight to the System 1 result than to the facts that produced it (Srull and Wyer 1980, 1983). Thus, an erroneous System 1 result has greater influence on our subsequent System 2 conclusions than the factual information (Dennis and Minas 2018).

In summary, we argue that placing a fake news flag on a story aligned with a user's beliefs will trigger cognitive dissonance. If the dissonance is strong enough, the user will invoke System 2 and expend greater cognitive effort to consider the headline and the fake news flag. The use of System 2 cognition will be indicated by the user taking more time to make a judgment about whether to believe the story or not, and by cognitive activity in certain brain regions. Our study uses the neurophysiological responses measured by EEG as an indicator of cognitive activity. We focus on activity in the frontal cortex because it is linked with cognitive activity associated with what we commonly consider to be "thinking": arousal, memory encoding, memory retrieval, insight, and consciousness (Başar et al. 1999; Klimesch 2012; Krause et al. 2000; Minas et al. 2018; Pizzagalli 2007). Thus, two indicators that this cognitive dissonance has triggered System 2 cognition will be more activity in brain regions associated with deliberate cognition, and more time taken considering the headline. Therefore:

H1a: Social media users will exhibit increased cognitive activity in brain regions associated with deliberative, conscious thought (i.e., System 2) when seeing a fake news flag on a headline aligned with their beliefs.

H1b: Social media users will spend more time considering the headline when seeing a fake news flag on a headline aligned with their beliefs.

Processing text arguments usually requires System 2 cognition because it requires deliberate attention to detail (Evans and Stanovich 2013; Kahneman 2003, 2011). It is simple to read a piece of text and pay little attention to its meaning by relying on System 1. However, for detailed information to be understood and integrated into the user's mental model, System 2 cognition is required (Evans and Stanovich 2013; Kahneman 2003, 2011).

We theorized that the cognitive dissonance created by the fake news flag will trigger System 2 cognition (H1). System 2 cognition enables the user to critically read the headline and the flag to understand their meaning. System 2 cognition will be more skeptical of the flagged headline than System 1 because System 2 is influenced less by confirmation bias than System 1 (Kahneman 2011). This will cause a decrease in believability. Therefore, we theorize that the fake news flag will reduce credibility in the headline that it appears on.

H2: Social media users will perceive headlines aligned with their beliefs that are flagged as fake as being less credible.

Method

Participants

A total of 83 undergraduates were recruited from a large business core course. All were experienced with social media. Age ranged from 18 to 34 (mean 19.5) and 39% were female. Three reported being left-handed and since a third of left-handed people have differences in brain structure, we removed all three participants from our EEG analyses.

Task

Participants read 50 fact-based news headlines and assessed their credibility. The headlines covered 10 topics related to U.S. politics and were actually true or false. Forty headlines were designed to be possibly true or false, though verifiably one or the other (e.g., Trump defunds Planned Parenthood, minimum wage should be $21.72 to keep pace with inflation). Ten headlines were controls intended to be more clearly true (e.g., Trump launches Twitter tirade; Hollywood celebrities oppose Trump). See Appendix A for headlines. Participants spent an average of 10.5 seconds reading each headline before beginning to answer questions about it.

Treatment

The experiment mimicked the Facebook display, although participants were not able to like, comment, or share the story. A flag matching Facebook's fake news flag was randomly assigned to 20 of the 40 non-control headlines (including those actually true) (see Figure 2).

Figure 2. Fake News Flag on a Facebook Headline

Measures

The primary behavioral dependent variable was the credibility of the headline, measured using three 7-point items from Beltramini (1988): believability, credibility, and convincingness. The Cronbach alpha was 0.94, indicating adequate reliability.

The second behavioral dependent variable was the time participants took to form their credibility assessment. The time was measured from the initial display of the headline until the participant clicked a button to display the credibility questions.

The alignment of a headline with the participant's political beliefs was coded as a binary variable; headlines positively supporting the participant's beliefs were coded as a 1; headlines that did not were coded as 0. We used 10 sources of self-reported data to assess the extent to which a headline aligned with participants' political beliefs. The participants reported their political affiliation on a 4-point scale (Democrat, Independent leaning Democrat, Independent leaning Republican, and Republication), which was collapsed into either Democrat (first two responses) or Republican (second two responses). They reported who they would vote for (Clinton or Trump) if the 2016 presidential election was held today. The election had been held four to six months prior. They also answered eight items (7-point scale, with 4 as neutral) measuring their political conservatism (Everett 2013). Our sample was fairly balanced politically, with 47% being self-reported Republicans and 53% Democrats; 31% reported that they would vote for Trump at the time of the study. See Appendix B for more information.

Two raters independently matched the headlines to the single most closely matching item out of the 10 political belief items and agreed on 46 of the 50 headlines (92%); differences were resolved. For example, an antiabortion headline was matched to the anti-abortion item (with those scoring 5–7 being susceptible to confirmation bias). A gun-rights headline was matched to the gun-rights item. A Trump-supporting headline was matched to a Trump voter.

Changes in cognition were measured using time-frequency analysis of EEG data. EEG enables the examination of neurophysiological changes that occur during information processing on the order of milliseconds (Berger 1929). EEG measures small electrical signals produced in the superficial areas of the underlying cortical regions. These electrical signals form complex wave patterns at specific frequencies that are related to cognitive activity. Berger's early research showed the importance of the alpha wave and its potential to indicate specific mental processes, including arousal, memory, and consciousness (Pizzagalli 2007).

A 2012 review concluded that alpha-band waves (8–13 Hz) indicate brain activity across many brain regions (Klimesch 2012). Alpha waves have been shown to change reliably in response to stimuli (Klimesch 2012). When a region of the brain becomes active, alpha waves desynchronize, leading to lower alpha levels (Cohen 1995); thus alpha wave desynchronization indicates higher levels of cognitive activity (Kelly et al. 2006; Klimesch 2012; Makeig et al. 2002). The upper alpha frequency band (~10–13 Hz) shows encoding memory processes in the parietal and frontal cortex regions (Kilner et al. 2005; Klimesch et al. 1997; Klimesch et al. 2001; Klimesch et al. 1996; Moretti et al. 2013).

We use time-frequency analysis, event-related spectral perturbation (ERSP), to analyze event-related desynchronization (Makeig 1993). It is important to note that, despite the similar acronym, time-frequency analysis (e.g., ERSP) differs from traditional event-related potential (i.e., ERP) studies in that it examines a frequency band (e.g., alpha wave) over a specified time-period. ERP examines specific waveforms that occur at a specified time period (e.g., P300 is a positive spike in neural activity that occurs 300 milliseconds after a rare event). In time-frequency analysis, we look for a pattern of changes (i.e., spectral changes) over a period of several seconds. We analyzed the last 4 seconds the participant viewed the headline to account for the time participants read the headlines. The alpha frequency band was examined for significant desynchronization in the 10–13 Hz frequency band as has been suggested and done in prior research (Minas et al. 2014; Müller-Putz et al. 2015). See Appendix C for more details.

We used a 14-channel Emotiv wireless EEG device (see Figure 3). We removed all artifacts and interpolated data. There has been debate within the cognitive neuroscience community about the validity of low-cost EEG systems like Emotiv. Many studies have scrutinized the Emotiv device in a variety of settings such as examining working memory (Wang et al. 2016), auditory analysis (Badcock et al. 2013), mobile brain–computer interfaces (Debener et al. 2012), detection of the P300 wave (Ramírez-Cortes et al. 2010; Wang et al. 2016), human–computer interaction (Taylor and Schmidt 2012), and hemispheric asymmetry (Friedman et al. 2015). These studies have found Emotiv to obtain a reliable and valid signal of underlying cortical activity as good as larger high-density systems albeit with lower spatial resolution so that the edges of regions are not as sharp and clear.

With time-frequency analysis, the researcher does not choose what brain regions to study. Results are presented for any regions that show significant differences, so a challenge occurs when differences are found in a region about which the researcher did not theorize. In this case, the researcher must interpret what activity in that region means and there are often several possible interpretations because each region performs many activities (Poldrack 2011). This has been called the reverse inference problem (Poldrack 2011). Reverse inference requires the use of abductive reasoning (Dubois and Gadde 2002; Peirce 1932), which is commonly used to develop theory, especially when unexpected empirical results are present (Van de Ven 2007).

Results

Behavioral Results

We used hierarchical linear modeling (HLM) to analyze the credibility and time data (see Table 1). Confirmation bias is present, with participants more likely to believe headlines to be credible when they aligned with the user's political beliefs ($t(4150) = 2.46$, $p = 0.014$). The fake news flag (Flagged as False) had no effect ($t(4150) = 0.52$, $p = 0.601$). Surprisingly, participants were more likely to believe that true headlines were *less* credible ($t(4150) = 2.45$, $p = .014$). We note that participants had difficulty assessing whether headlines were true or false; they correctly assessed only 44%. Participants spent 1.4 seconds longer considering a headline when the headline was flagged as false ($t(4150) = 3.32$, $p = 0.001$), and an additional 1.9 seconds when the headline was flagged as false and the headline aligned with their beliefs ($t(4150) = 2.45$, $p = 0.014$).

These results support H1b (that users take more time when seeing a fake flag on a headline aligned with their beliefs). However, H2 was not supported: the fake news flag did not reduce the credibility of headlines aligned with beliefs.

Neurophysiological Results

We examined the cognition triggered by a headline that supported the participant's beliefs but was flagged as being false. When a brain region is active, desynchronization of neural activity in the alpha band occurs (called "alpha blocking") (Potter and Bolls 2012), thus event-related desynchronization (ERD) is an indicator of cognitive activity. ERSP analysis produces a set of areas within the brain (called clusters) showing the location of ERD and whether there are significant differences between the treatments. The clusters identified by the analysis may or may not align with the regions about which the researcher has hypothesized, and may span several distinct brain regions, making interpretation challenging. However, when a cluster includes a theorized region, it is a powerful signal supporting the theory, because nothing

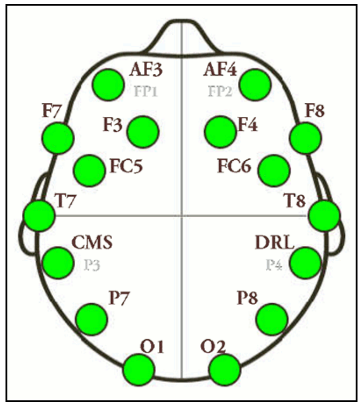


Figure 3. Position of the Electrodes on the EEG Headset with Labels Along the 10–20 System

Table 1. Behavioral Outcomes

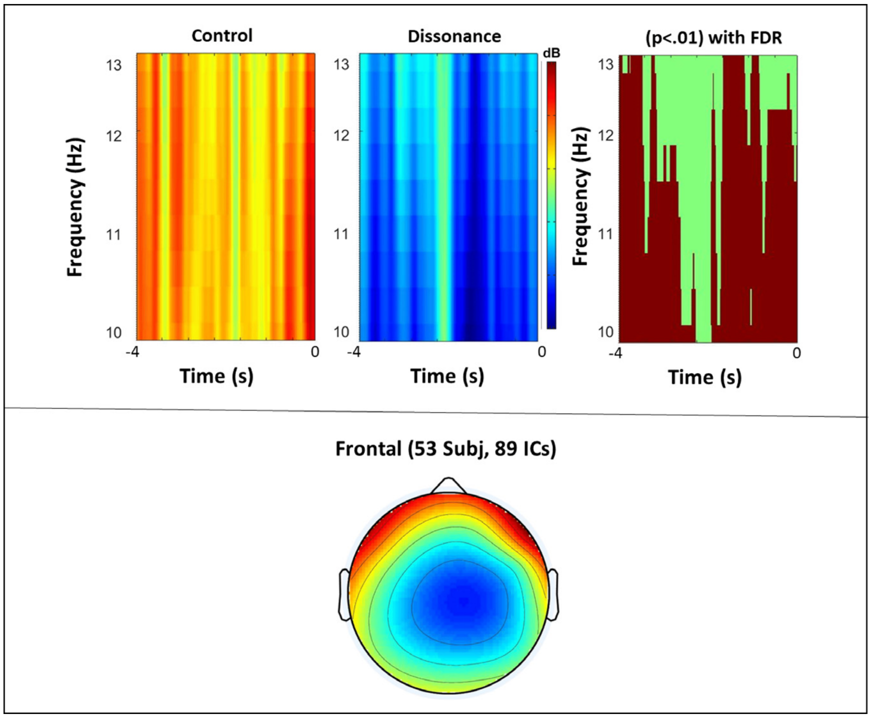
	Perceived Credibility		**Time Spent in Seconds**	
Factor	**Coefficient**	**P-value**	**Coefficient**	**P-value**
Intercept	3.328***	0.000	8.166	0.062
Political Party (Democrat = 1)	0.312*	0.016	-0.913	0.248
Gender	0.053	0.689	0.169	0.836
Age	0.012	0.738	0.116	0.598
Aligned with Beliefs	0.177*	0.014	-0.637	0.179
Actually True	-0.130*	0.014	-0.064	0.855
Flagged as False	0.033	0.601	1.364***	0.001
Flagged × Aligned with Beliefs	-0.035	0.762	1.884*	0.014

Note: *p < .05, **p < .01, ***p < .001

in the analysis directed the software to consider the theorized region; the region emerged from the data.

Our analysis produced two clusters with significant differences that suggest participants experienced cognitive dissonance. The first cluster was as hypothesized in frontal cortices (see Figure 4). Participants showed significantly more activity in the frontal cortices for headlines that supported their beliefs but were flagged as false. The differences are across the upper alpha band and are spread throughout the time period. Increased activity in the frontal cortices is associated with increased cognitive activity, including arousal, memory, and consciousness (Pizzagalli 2007) and arousal, memory access, and consciousness (Başar et al. 1999; Krause et al. 2000; Pizzagalli 2007). The frontal cortices are active during deliberate cognitive tasks and high-order cognitive processes (Başar et al. 1999; Kilner et al. 2005; Klimesch et al. 1997; Klimesch et al. 2001; Klimesch et al. 1996; Krause et al. 2000; Moretti et al. 2013). This indicates that participants utilized more cognitive activity considering headlines that supported their beliefs but were flagged as false than other headlines.

The second cluster also shows activity in the frontal cortices, but also includes some activity in the right parietal region, about which we did not theorize (Figure 5). There are several possible interpretations. Activity in the right parietal can indicate encoding and retrieving a stimulus in working memory (Foxe and Snyder 2011; Gevins et al. 1997; Mevorach et al. 2006). It can indicate directing attention toward salient stimuli (Foxe and Snyder 2011; Mevorach et al. 2006), and turning toward a stimulus (rather than away) (Schutter et al. 2001). It has also been linked to sustained attention to a stimulus being retained in working memory and encoding or retrieval of semantic memory (Gevins et al. 1997; Klimesch et al. 1997; Klimesch et al. 2001). In this case, all three interpretations provide a similar conclusion: individuals paid more attention to headlines supporting their beliefs that were flagged as false.



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. (See appendix file for color image.)

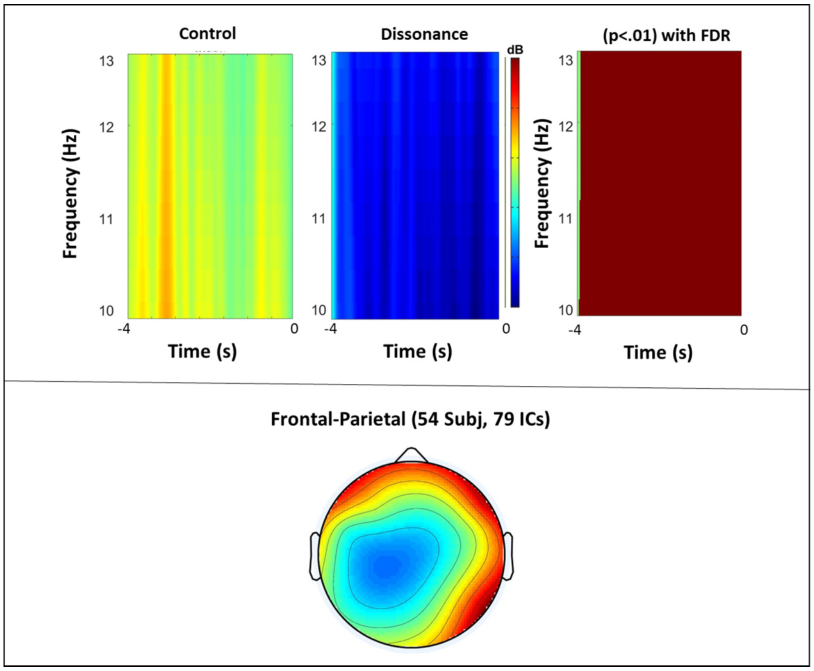
Figure 4. Differences in Frontal Cortices Cluster Due to Cognitive Dissonance

Taken together, these two clusters indicate that participants spent more cognitive effort considering a headline that supported their beliefs but was flagged as false compared to other headlines (e.g., those supporting their beliefs but not flagged, or challenging their beliefs—flagged or not). This increased cognitive activity also corresponds to the increased time that subjects spent on these headlines (Table 1). The EEG analysis supports the time evidence that a fake news flag creates cognitive dissonance and prompts users to think more. Although users did not perceive the flagged headlines as less credible, this pattern suggests that a fake news flag designed to have a stronger message may be effective on social media.

Post Hoc Analysis on Confirmation Bias

We conducted a *post hoc* analysis investigating cognition in the presence of confirmation bias, because past research in a different context (virtual team decision making— a utilitarian mindset) has found that individuals are more likely to engage in cognitive activity when they encounter information that supports their opinions and simply ignore information that opposes them (Minas et al. 2014). This context is different because social media users are in a hedonic mindset (Chauhan and Pillai 2013). Hedonic and utilitarian motivation have been shown to have differential effects on confirmation bias (Borrero and Henao 2017; Stone and Wood 2018).

This *post hoc* analysis found increased cognitive activity in two clusters when participants saw headlines aligned with their opinions (i.e., when confirmation bias was present): the frontal cortices (Figure 6a) and the right parietal and somatosensory region (Figure 6b). Increased activity in the frontal cortices is linked to increased higher order cognitive processes, while increased activity in the right parietal is linked to focusing attention. Increased activity in the somatosensory region has been linked to motion, planning for motion, or tactile sensations (Hari et al. 1998; Porro et al. 1996), which is hard to interpret. We conclude that once participants realized that a headline supported their opinions, they directed attention to it, but when they realized that a headline challenged their opinions, they did not direct attention to it.



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. (See appendix file for color image.)

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

Discussion

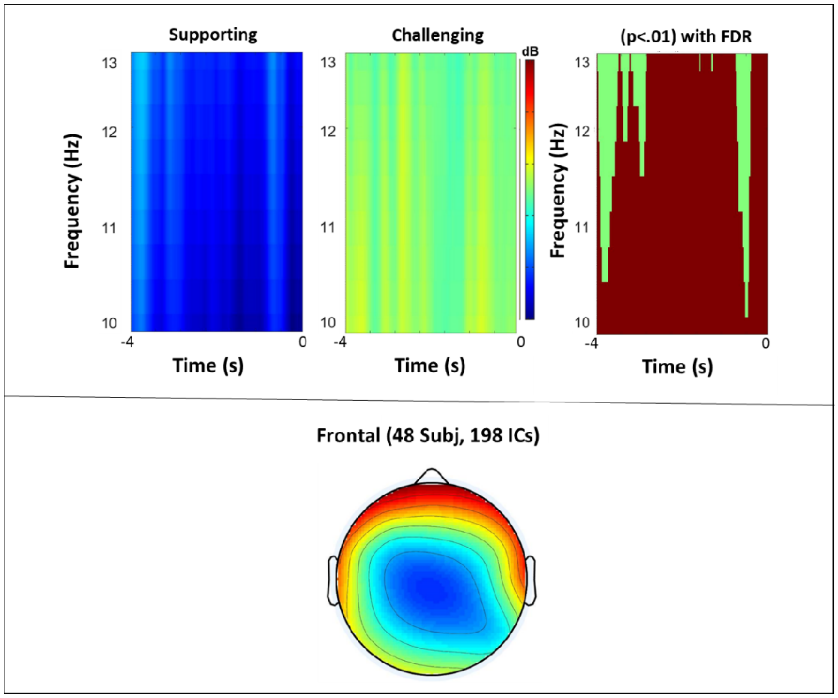
Our study examined whether a fake news flag helped social media users discern true news from fake news. The fake news flag did not influence user beliefs, although it triggered more cognition and increased the time spent considering the headline. This suggests that some cognitive dissonance was created by the fake news flag, although not enough to alter beliefs. Instead, users were more likely to believe news headlines they wanted to be true (see Table 2).

We see three key conclusions. First, the presence of a fake news flag did not affect how participants perceived the credibility of the headlines. The time and EEG results indicate that the flag caused cognitive dissonance and induced participants to think more deeply about the truth of the headline. However, the cognitive dissonance triggered by the flag was not enough to overcome participants' inherent confirmation bias; although they thought more, this additional thought did not cause them to believe the headline less. The flag was simply not strong enough to make users overcome their *a priori* beliefs. Perhaps in the era of fake news, users are more likely to dismiss information that challenges their opinions as being fake. This fake news flag is an ineffective remedy for fake news; again, we note that Facebook discontinued its use in 2017 (Meixler 2017).

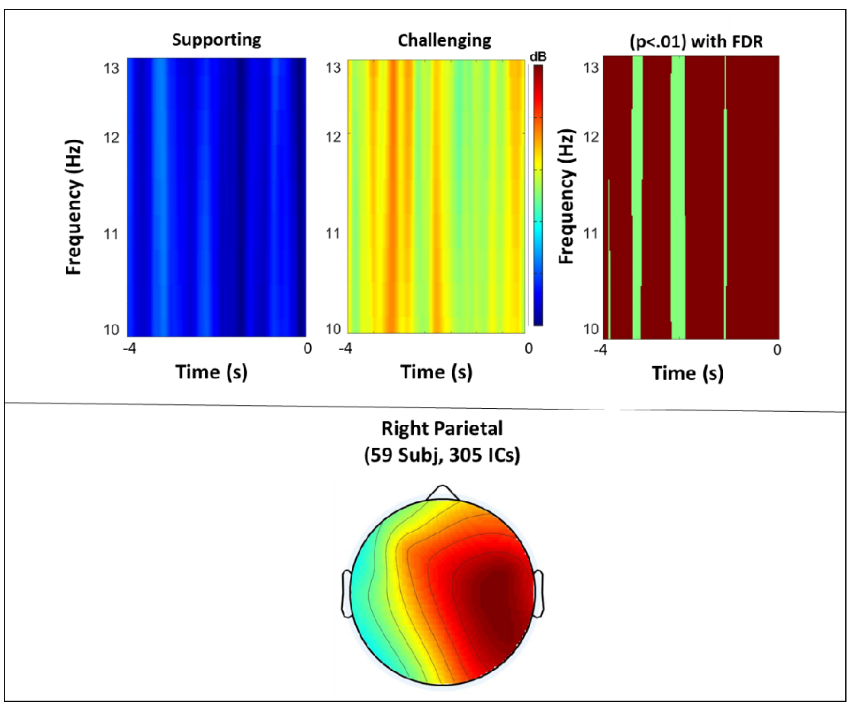
Second, confirmation bias drives beliefs. Participants were more likely to believe and think about headlines that aligned with their beliefs. Rather than expend cognitive effort to consider the actual truth of the article, participants rejected reality in favor of their *a priori* beliefs (Allcott and Gentzkow 2017; Koriat et al. 1980; McKenzie 2006; Nickerson 1998). We confirm that social media is highly subject to confirmation bias.

Third, the objective, underlying truth of the headlines had little effect on whether participants believed the headlines or not. Participants were not more likely to believe headlines that were verifiably true. It may be that an increased awareness of fake news may have caused participants to be naturally more skeptical of all headlines presented; the mean credibility score of 3.7 (on a 7-point scale) across all headlines suggests a slight bias toward skepticism.

We used EEG to complement other sources of data such as self-reported data (i.e., belief in the headlines) and observed data (i.e., time taken). The primary advantages of this data



(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). (See appendix file for color image.)

Figure 6. Differences Due to Confirmation Bias

Table 2. Summary of Results

Hypothesis	Description	Supported
H1a	Social media users will exhibit increased cognitive activity in brain regions associated with deliberative, conscious thought (i.e., System 2) when seeing a fake news flag on a headline aligned with their beliefs.	Yes
H1b	Social media users will spend more time when seeing a fake news flag on a headline aligned with their beliefs.	Yes
H2	Social media users will perceive headlines aligned with their beliefs that are flagged as fake as being less credible.	No

are that they are generally not susceptible to subjectivity bias, social desirability bias, and demand effects (Dimoka et al. 2012). The use of three distinct types of data enabled us to triangulate across the different sources to better understand the phenomenon (Dimoka et al. 2012). The EEG results support and extend the behavioral results and suggest that the fake news flag worked as intended in triggering greater deliberate cognition but was not strong enough to overcome *a priori* beliefs. This suggests that the flag may need to be stronger in design to have a major impact on beliefs.

Theoretical Implications

First, our research shows that the fake news flag triggered more cognitive activity and caused users to spend more time when the flag was placed on headlines they wanted to believe. This indicates that fact-checking may have promise, because it triggered deeper cognition. This supports our theorizing that a fake news flag can create cognitive dissonance and trigger users who are not in a critical mindset into thinking more carefully. Thus, we can design technology to deliberately change user cognition. We need more theory and research on how technology can deliberately alter user cognition. Changing user cognition is not normally a technology design principle, but perhaps it should be. One might argue that more System 2 cognition is always better, but this is not the case; using technology design to trigger System 2 cognition should be used judiciously, as too much System 2 cognition is tiring (Kahneman 2011).

Second, despite the increased cognition triggered by the fake news flag, it did not change users' beliefs. It may be optimistic to believe that a simple "disputed" flag might trigger the deep introspection needed to overcome confirmation bias and resolve cognitive dissonance. Thus, we need more theory and research on fake news and how to develop stronger signaling mechanisms for the results of fact-checking, ones that might be strong enough to overcome confirmation bias. Perhaps this could be a different flag with stronger words, or a different type of intervention.

Third, we found that confirmation bias is a significant problem on social media. It persists even in the face of design features intended to combat it. Users read and think about headlines confirming their beliefs, and ignore headlines that challenge them; confirmation bias is so strong that users simply do not think about information they do not like. The often quoted remedy for fake speech is to offer more true speech (see U.S. Supreme Court Justice Brandeis' comments in his Whitney v. California opinion; Supreme Court 1927). Our results suggest that this remedy, at least on social media as currently designed, will fail. Confirmation bias is more influential on social media than we expected, as it has consequences for what we do not pay attention to (i.e., information challenging beliefs). In addition to more theory and research about stopping belief in fake news, we need more theory and research on how to enable true speech to be heard. How can we change social media to encourage users to engage with stories that challenge their beliefs?

Finally, these results add to the growing understanding of the importance of context on technology use. In the hedonic context of social media use, System 1 cognition plays a major role, with System 2 cognition used occasionally. We show how EEG can detect System 2 processing by finding increased cognitive effort in the frontal cortex. Most information systems theories assume a deliberate, thoughtful, decision maker, yet this was not often true for our social media users. We need more theory and research about the role of context in technology use, especially about the user's mindset while using technology and its effects on cognition.

Implications for Practice

Facebook's fake news flag had no effect on beliefs. It did not induce participants to conclude that a news article was less credible. They spent more time when a headline they supported was flagged as fake, but the flag did not change their beliefs. Perhaps more importantly, the actual truth of a headline did not influence users' beliefs; users were generally unable to accurately separate true news from fake news. We conclude that we need to develop a better method for warning social media users of fake news.

People will continue to consume news on social media and will continue to struggle to determine its truthfulness. The sheer volume of fake news on social media (Silverman 2016) means that this problem is unlike any we have seen before; "quantity has a quality all its own" (commonly attributed to Josef Stalin). There are real and demonstrable consequences from enabling the spread of posts that are verifiably false to spread disinformation or profit from users' gullibility (House of Commons 2018). We believe that Facebook and other social media firms have a responsibility to better enable users to discern truth from fiction (see House of Commons 2018).

Limitations

We began by theorizing that the context of social media is important; social media use is often hedonic as users browse on cell phones while waiting in line, on laptops while watching TV, and so on. Yet we studied use in the cold, clinical context of a lab experiment, where we could carefully control exogenous factors. This setting may have triggered a utilitarian mindset of thinking more deliberately than the normal, everyday setting of social media use. Thus, the effects observed in the lab may be understated; the real problem may be worse.

Our study suffers from the usual limitations of lab studies. We studied undergraduates, who may not be representative of the general population (Koriat et al. 1980). They had experience with social media, but care should be taken when generalizing to populations that lack experience. The neuroanatomy of some young adults changes through their teens into their mid-20s, with neuroplasticity (i.e., changes to neural structures and networks) also prevalent in adulthood (Draganski et al. 2004; Sowell et al. 1999). We are unaware of any studies showing systematic differences in alpha attenuation between young adults and older adults.

Conclusion

Our results add to the growing list of evidence that fake news is a major societal problem. Many solutions have been proposed and many pundits have offered opinions. However, we have little empirical research on the effectiveness (or lack thereof) of the many proffered options. More research is needed on ways to improve social media users' ability to discern truth from fiction and on ways to induce social media users to invest more attention on the news they see.

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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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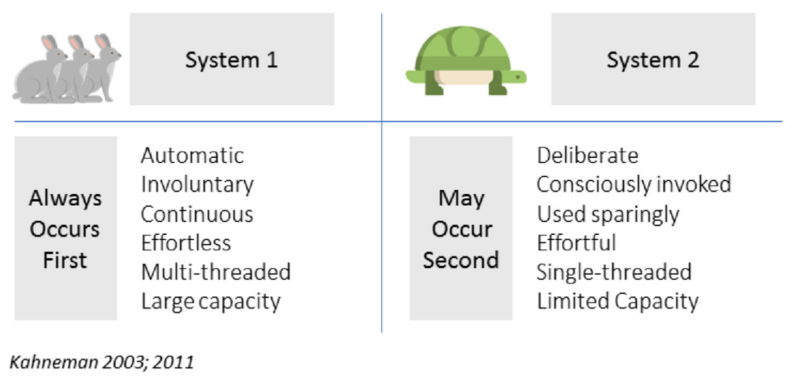


Figure 1. Summary of System 1 and System 2 Processing

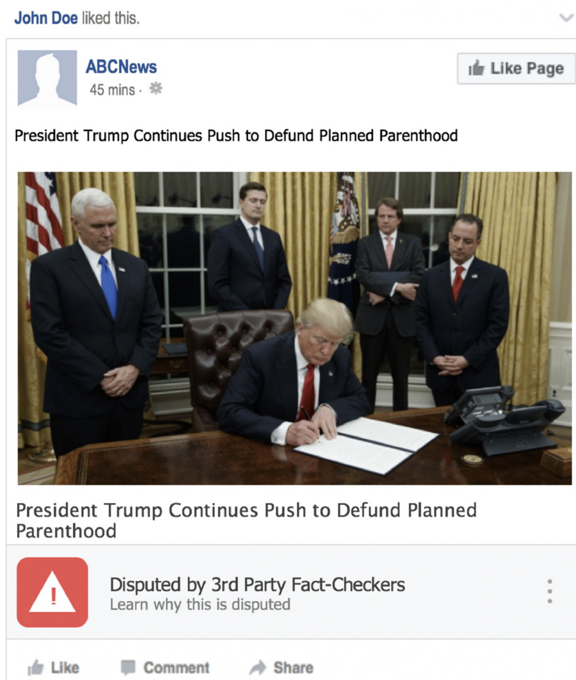


Figure 2. Fake News Flag on a Facebook Headline

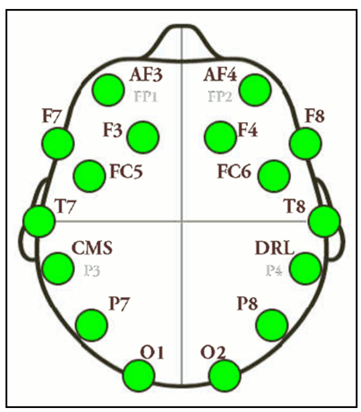
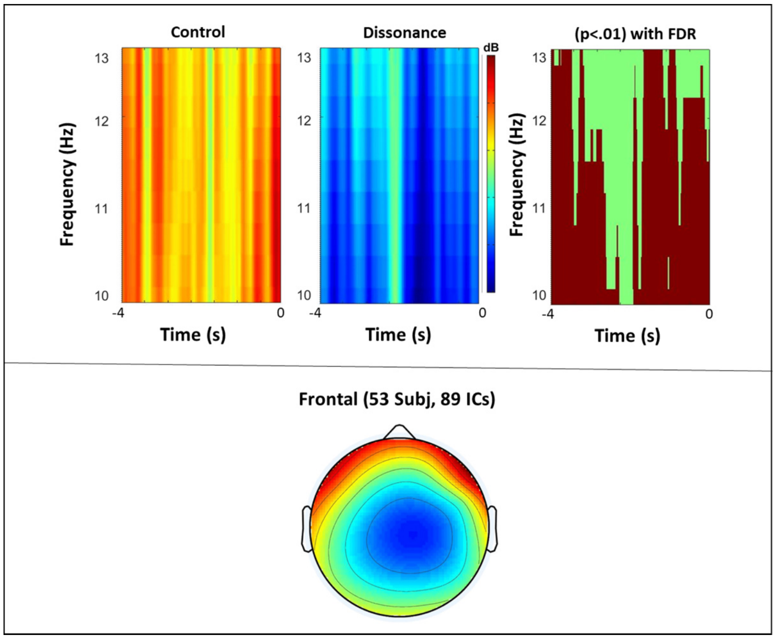
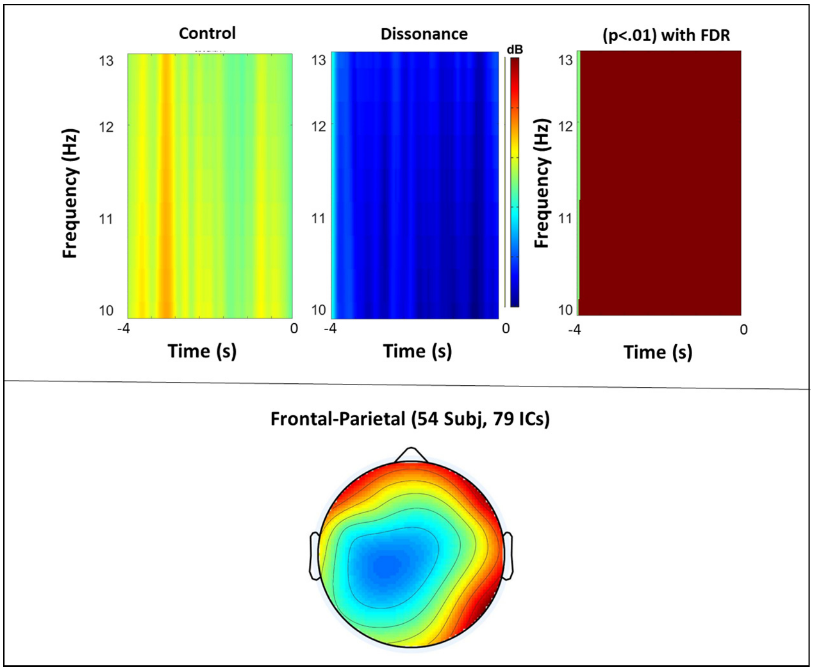


Figure 3. Position of the Electrodes on the EEG Headset with Labels Along the 10–20 System



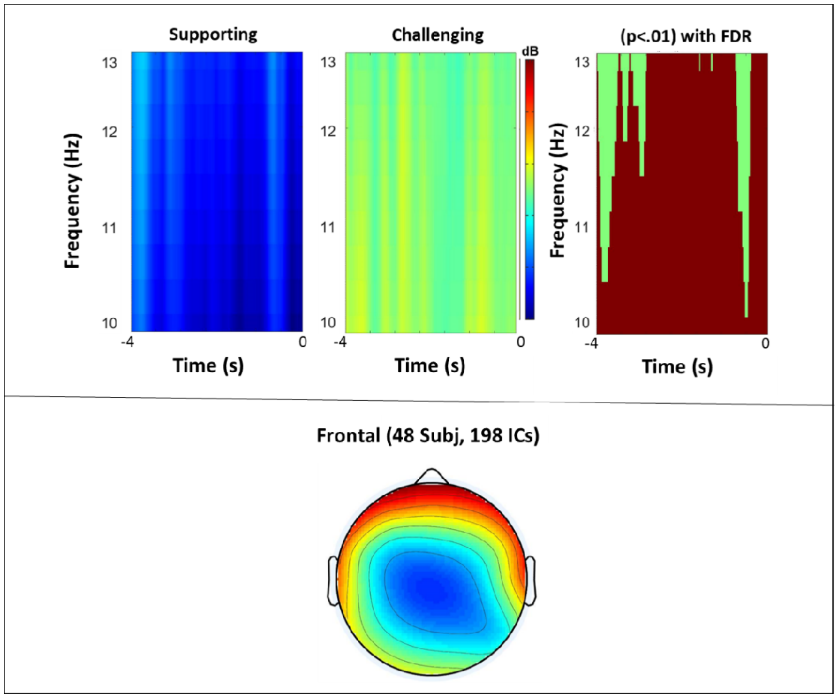
The top left and middle panels show alpha activation for headlines we theorize cognitive dissonance (ones that supported the participant's beliefs and were flagged as false (middle panel) versus all other headlines (left panel); cooler colors (i.e., blue) indicate greater cognition (i.e., greater event-related 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

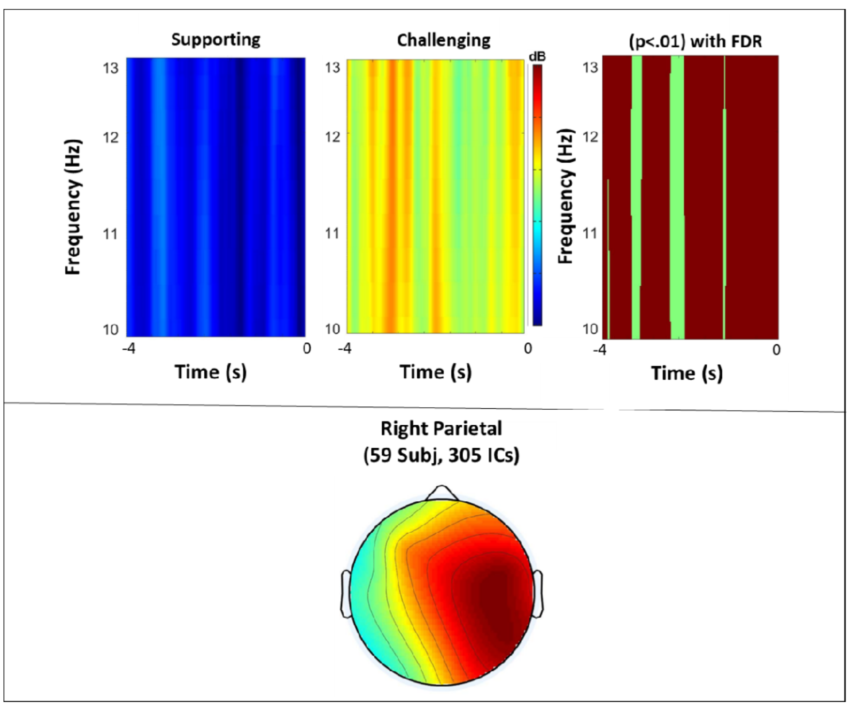


This analysis shows cognition for headlines that supported a participant's political beliefs and were flagged as false (middle panel) versus all other headlines (left panel); blue indicates greater desynchronization. The right panel shows significant differences (in red) between the two panels, at p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

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

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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