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EXPLORATORY STUDY ON TRUST, DISTRUST, AND CREDIBILITY IN MACHINE JOURNALISM

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Abstract

The current study investigated the effect of machine-generated journalism. Specifically, the effect of machine journalism compared to human journalist on the perceptions of credibility and distrust for news articles on controversial topics was explored. To further extend the well-established theories of credibility in journalism, this study introduced the concept of distrust as a construct that is distinct from credibility or trust. The relationship between trust and hostile media effect was explored. Finally, this study investigated if trust and hostile media effect are related to the perception of fake news. The results show that distrust was indeed distinct from credibility or trust in journalism context not only at a measurement level but also in terms of its effects on other constructs; trust and credibility lacked discriminant validity, suggesting the two are measuring similar psychological constructs; machines were perceived to be less trustworthy compared to human journalists; and strong relationships between trust/distrust/credibility and fake news were observed.

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Chapter 1: Introduction

Interactive media including computers, the internet, virtual agents, and algorithms for various tasks have become a crucial part of our lives today. With the recent advances in machine learning technology, both academia (Galily, 2018; Jung, Song, Kim, Im, & Oh, 2017; Linden, 2017; Thurman, Dörr, & Kunert, 2017) and industry (e.g., Peiser, 2019) recognize the increasing importance of artificial intelligence (AI) in our lives.

Journalism is one of the areas that are predicted to be impacted by automation. Researchers have discussed the current state of robot-assisted journalism (Galily, 2018; Jung et al., 2017; Linden, 2017; Thurman et al., 2017) and the future of AI assisted or stand-alone AI journalism (Miroshnichenko, 2018; Shekhar, 2017).

While the automation of journalism could bring cheaper production costs and enrich us with more information, it is yet unclear how people would appreciate news content created by machines. In certain cases, human hands are more appreciated than a cutting-edge technology; a handmade tourbillon watch that loses the time by seconds or even minutes per day is sometimes more appreciated than a cheap factory-made quartz watch that keeps the time almost perfectly.

In this context, the current study explores the effect of automated journalism in controversial news topics on news perception and its subsequent outcomes. Specifically, this study attempts to investigate if people perceive news differently in terms of credibility and "discredibility" if they are told that news articles on controversial topics are created by a machine compared to human journalists.

A growing body of literature focuses on machine journalism (Clerwall, 2014; Graefe, Haim, Haarmann, & Brosius, 2016; Liu & Wei, 2018; van der Kaa & Krahmer, 2014; Waddell, 2018; Zheng, Zhong, & Yang, 2018). As credibility is essential to the existence of journalism

(Kohring & Matthes, 2007), machine journalism research has also been focused on assessing credibility. Previous studies vary in terms of conceptualizing credibility as source credibility (i.e., the credibility of the sender of the message) or message credibility (i.e., credibility found within the message). Therefore, this present study proposes a systematic analysis that employs both source credibility and message credibility.

While message credibility refers to the credibility related to the news message itself (Appelman & Sundar, 2016), source credibility refers to the credibility perception of receivers on characteristics related to the source of the message (Hovland & Weiss, 1951). Considering that machine learning, which is thought as a subset of AI (Bini, 2018), only became technologically available recently, credibility in journalism has been mostly examined with the assumption that the source is human since Hovland and Weiss (1951) and thereafter. This means that we must clarify if people perceive machine as source (i.e., people have social reaction towards the machine as if they would do towards humans) to apply past findings regarding credibility. In other words, to apply social psychology to human's reaction towards AIs, algorithms, or its works requires a presupposition that humans treat computers as social entities.

CASA (computers are social actors) provides an answer to the orientation issue of machine journalism. Reeves and Nass (1996) have found that people tend to treat interactive media as social beings, namely CASA (computers are social actors). Since then, there has been a well-established line of research regarding CASA and the mechanism of this behavior: Nass and Moon (2000) found that such social response is automatic; and Sundar and Nass (2000) found that this reaction is directed toward the machine rather than the programmer behind it.

Another distinct line of research in social cognition found that humans inevitably tend to judge others through stereotyping, supported by empirical studies which employed techniques such as implicit association test (IAT; Greenwald, McGhee, & Schwartz, 1998; Greenwald, Poehlman, Uhlmann, & Banaji, 2009). Since people perceive computers are social beings, investigating how people perceive machine algorithms differently from humans may lead to finding whether people make a social stereotyping judgment about artificial intelligence.

This study also tests if people perceive the bias, or objectivity of machine journalism to be different from that of human journalists. Hostile media effect refers to a phenomenon where a neutral or balanced news report on a controversial topic is perceived as biased against their position from supporters of both ends of the issue (Perloff, 2015). Hansen and Kim (2011) speculated that media credibility or media trust (credibility or trust towards a certain media organization) contributes to hostile media effect. Additionally, they also suspected that hostile media effect might also be contingent upon perceived source credibility. This study thus explores if hostile media effect is related to source credibility and message credibility.

Additionally, this study attempts to investigate “negative credibility” as a concept that is distinct from credibility. In journalism studies, credibility typically has been either conceptualized as a value that possesses null-or-greater value only or treated as a singular concept with bipolar values.

However, studies from other disciplines, such as psychology (e.g., Tversky & Kahneman, 1991) and marketing (e.g., Dimoka, 2010), have found behavioral, cognitive, and neuropsychological evidence that suggest positive trust and negative trust (i.e., “distrust”) are distinct constructs, rather than polar constructs on a single conceptual pane. Similarly, previous research in communication also has shown that positive and negative message may function differently (Lang, Sanders-jackson, Wang, & Rubenking, 2013). As trust is a construct that is deeply related to credibility (e.g., Fletcher & Park, 2017; Shariff, Zhang, & Sanderson, 2017), this study proposes that through testing negative credibility (or "discredibility") as distinct variable from positive credibility by incorporating ideas from distrust literature, we may have a deeper understanding of news credibility and its relationship with hostile media effect.

Finally, by recognizing the increasing interest in fake news from the public and scholars in the past few years, this study attempts to explore the relationship between the perception of fake news and concepts of credibility, discredibility, and hostile media. Here, the perception of fake news differs from actual fake news, or fake news production. As much as the production and distribution of fake news is of concern to journalism (e.g., Lazer et al., 2018), understanding how people authenticate the information within news is of interest. Indeed, perception of fake news is thought to be related to credibility of the source (e.g., Tandoc et al., 2017). This study employs actual news with true information, with a supposedly neutral stance. In this case, high scores in perception of fake news may indicate that people may be selectively processing the information in the news article. In other words, significant relationships between hostile media effect and perception of fake news may suggest that perception of fake news may be a rationalization for their denial against the information people found in news.

The relationship between machine journalism, credibility, and perception of fake news is also of interest in the current investigation. Past research found differences in terms of credibility between machine journalist and human journalist partly because of different expectancy we have for the two (Waddell, 2018). A crucial element to judge a journalistic work to be fake news is for the news to convey an intention to deceive (Tandoc, Lim, & Ling, 2018). Because perceived intention of the source is an important factor for source credibility (trustworthiness) and trust (benevolence/malevolence), difference in credibility or trust for machine versus human journalists may result in difference in terms of perception of fake news for machine versus human journalists.

In sum, this dissertation investigates the distinctive effect of positive and negative credibility in machine-generated news articles on hostile media effect and the perception of fake news.

Chapter 2: Literature Review

Overview

Computers are social actors (CASA) paradigm is utilized as a theoretical background for comparing works of machine versus human as if machines were social entities. Previous researches on machine journalism investigated the effect of machine authors of news articles on credibility compared to that of human journalists. Reports from these studies show contradicting results for credibility. While journalism studies recognize credibility to be a multifaceted construct, some of the earlier research in machine journalism might have overlooked the intricate nature of credibility in journalism, which might have contributed to the mixed results among earlier studies. Thus, credibility is dissected in machine journalism context by differentiating source credibility, message credibility, trust, and distrust.

Previous machine journalism studies share similar type of news articles, which are data-driven straight news (e.g., sport game results, finance news, or weather). In an effort to extend previous findings, by following recommendations from earlier researches (van der Kaa & Krahmer, 2014), the current study employs news articles with controversial topics as stimuli to investigate the effect of machine journalism on credibility. As this study employs news articles with controversial topics as stimuli, hostile media effect, a phenomenon where supporters of both sides of controversies have a tendency to view neutral or balanced news articles to be biased against their belief (Perloff, 2015), is also investigated. Finally, perception of fake news is also investigated, because credibility and hostile media effect are thought to be related to perception of fake news.

Computers Are Social Actors (CASA)

To compare our perception towards the works done by machines versus humans, the locus of the effect for the two conditions should be equivalent. That is, for the current study to compare the credibility perceptions of works done by machine versus human, the credibility should be targeted towards the machine itself as if it was a social entity, as we do for human. However, some previous studies on the source orientation of human-computer interaction (e.g., Sundar & Nass, 2000) have proposed (but not supported) an idea that the social perception of machine or computers could be actually directed at the humans behind it (i.e., programmers for the interface, algorithm, computer, or machine). It is necessary to pinpoint the locus of credibility since in communication studies, credibility for the elements of communication (e.g., source, message, or channel; McGuire, 1978) are thought to be distinct (e.g., source credibility and message credibility are distinct). If the source credibility of an algorithm is mostly impacted by the perceived credibility of the programmer behind the algorithm, this suggests that additional element for human-machine communication exists (i.e., "programmer" before sender), and the validity for comparing the credibility of humans and machines directly would be undermined.

The CASA (Computers Are Social Actors) paradigm, coined by Nass, Steuer, and Tauber (1994), suggests that people apply the same social rules between humans such as reciprocation (Nass, Fogg, & Moon, 1996), gender stereo types (Nass, Moon, & Green, 1997), and specialist versus generalist perception (Nass & Moon, 2000), to human-computer interaction. Also, research based on CASA found that people's responses to computers are essentially social and natural (Nass & Moon, 2000). Pertinent to the current study, CASA can be applied to text-based communication, as text-based communication provides enough cues for people to interact with computers as social actors (e.g., Nass & Moon, 2000; Nass et al., 1994; Reeves & Nass, 1996).

There are two explanations for CASA: *anthropomorphism* and *mindlessness.* The anthropomorphism explanation suggests that people tend to imbue nonhuman agents with human-like characteristics (e.g., Epley, Waytz, & Cacioppo, 2007). On the other hand, the mindlessness explanation (e.g., Nass & Moon, 2000) purports that people, as cognitive misers, tend to focus on social cues over asocial cues during human-computer interaction. The difference between mindlessness and anthropomorphism explanations is possibly the cognitive load that is thought to be related to processing CASA. Through series of experiment, Nass & Moon (2000) demonstrated that mindlessness better explains the phenomenon than anthropomorphism.

Together, the literature on CASA suggests that in the context of machine-generated journalism, people's reaction towards algorithms is a result of perceiving them as sources (i.e., the source orientation is towards the machine and perceive it as a social entity), rather than a reaction towards a programmer behind the algorithms as shown by previous studies (Nass & Moon, 2000; Sundar & Nass, 2000). Additionally, CASA indicates that there is minimal cognitive effort involved in treating computers as if they were social actors since CASA is a mindless process (Nass & Moon, 2000). Taken together, CASA suggests that perceptions of machine journalism versus that of human journalism is comparable, and social psychology constructs can be applied to interactions between human and machines, as people react socially towards machines (and not the programmers or other related humans under the hood) as if they were social actors without spending significant cognitive effort.

Previous Studies on Machine Journalism

Numbers of studies were conducted on the relationship between machine-written news articles and the readers' perception. Earlier studies (Clerwall, 2014; Graefe et al., 2016; van der Kaa & Krahmer, 2014) investigated the current state of algorithm-driven news production. They tested data-driven news articles (e.g., sports results and financial news in text), which are currently in use. Clerwall (2014) was one of the first to empirically explore the effect of robot-written news article on credibility compared to that of humans. Clerwall (2014) reported that robot-written articles are perceived to be more credible, while human-written articles are thought to be more coherent, better written, clearer, less boring, and more pleasant to read. van der Kaa and Krahmer (2014) investigated whether there is an occupational bias between consumers and journalists in perception of machine-written vs. human-written news in terms of expertise and trustworthiness by comparing responses from a group of journalists and a group of consumers. In their 2 (occupation, journalists vs. consumers; between) x 2 (author, machine vs. human; within) within and between design experiment, they found that the journalist group perceived expertise to be higher on both machine and human author conditions than consumers did. There was no difference in the consumer group's perception of robot- and human-written articles in terms of expertise; the journalist group perceived human-written articles to be more trustworthy.

While Clerwall (2014) and van der Kaa and Krahmer (2014) share credibility as their dependent variable, they differ in terms of their method of manipulation. Clerwall (2014) employed articles that were actually generated by humans or machines but did not declare the author information to its participants. On the other hand, all of the articles that were used in van der Kaa and Krahmer (2014) were generated by machines while participants were told that each article was either written by a machine or a human author. Graefe et al. (2016) corroborated and replicated previous findings from Clerwall (2014) and van der Kaa and Krahmer (2014); using 2 (topic, sports vs. finance; within) x 2 (actual source, human vs. machine) x 2 (declared source, human vs. machine) factorial design, they varied actual sources (i.e., actual author of the article) and declared sources (i.e., author information provided to the participant) among conditions to test whether there is a difference in perceptions of credibility, expertise, and readability. When the source was declared as human, articles were perceived to be higher in all three dependent variables of credibility, expertise, and readability. When actual sources were compared, credibility was higher for robot-written articles, and readability was higher for human-written ones, while there was no difference in terms of expertise.

More recent studies extended and substantiated previous findings of earlier studies. Zheng et al. (2018) investigated whether there is a cultural difference between accepting robot-writers and human-writers. They found that Chinese readers preferred news written by robots, while U.S. readers chose human reporters. Waddell (2018) further investigated the psychological underpinnings of how people perceive machine-laden journalism. The study hypothesized that news credibility for machine and human authors differs, and this would be affected by anthropomorphism and expectancy violation theory. Expectancy violation theory posits that violation of expectation occurs when the communicator's action fails to meet our prior standards, by either expectation being exceeded (i.e., positive expectancy violation), or rejected (i.e., negative expectancy violation). Using data-driven news articles similar to earlier studies (Clerwall, 2014; Graefe et al., 2016), Waddell (2018) found that human journalism scored significantly higher on credibility, newsworthiness, quality, and representativeness than machine journalism. Additionally, Waddell (2018) reported that the effect of machine journalism operated indirectly through pathways of source anthropomorphism and negative expectancy violations. Waddell (2018) assessed message credibility (Appelman & Sundar, 2016), which differs from earlier studies which did not specify the domain of the credibility. Components of credibility is reviewed in the following section.

Earlier studies (Clerwall, 2014; Graefe et al., 2016; van der Kaa & Krahmer, 2014) focused on analyzing the state-of-the-art of machine journalism by employing currently available stimuli, data-driven journalism (e.g., sports, finance, and weather). Recognizing this theme, van der Kaa and Krahmer (2014) suggested exploring the effects of story topic for future studies. Liu and Wei (2018) employed diverse topics as stimuli including Obamacare, LGBT rights, and refugee admission, and compared New York Times (NYT) and Fox, spot and interpretive news types. Result shows that overall credibility was higher for NYT than Fox across topics. Key findings in this study was that machine journalism was perceived to be more objective but of less expertise compared to human journalists regardless of other conditions; machine journalism enhanced perceived objectivity for NYT while worsened perceived expertise and trustworthiness for Fox; and while interpretive news were perceived to be significantly more credible than spot news for machine writers, this difference was insignificant for human authors.

In sum, with some exceptions, the results from prior studies mostly focused on data-driven journal articles that are currently in use, actually or purportedly. All of the past studies include credibility as part of the key variables. Most studies investigated reader evaluations including credibility, readability and expertise, and others including trustworthiness, likeness, accuracy, and authenticity, among others. The result regarding credibility or trust varies between studies, in that some studies found machine journalism to be more credible while others found human journalists to be more credible. As van der Kaa and Krahmer (2014) suggested, this study attempts to test the impact of machine journalism using more controversial topics as stimuli.

Credibility in News

Credibility is essential to the existence of news media. Or, at the very least, there is a widespread belief that audiences are more inclined to consume news provided by credible sources (Thorson, Vraga, & Ekdale, 2010). Accordingly, research on credibility has a long history (e.g., Giffin, 1967; Hovland & Weiss, 1951; Meyer, 1988).

As source, message, channel, receiver, and destination are identified as distinct components of communication (McGuire, 1978), the credibility of each has been conceptualized and analyzed as discrete variables. Among these, the current study focuses on source credibility and message credibility.

Credibility has primarily been defined as the credibility of the source (Gunther, 1992). Two components of source credibility are thought to be most important - *expertise* and *trustworthiness* (McGinnies & Ward, 1980; Pornpitakpan, 2004). Expertise is defined as the communicator's ability to confer accurate information (i.e., the source is knowledgeable enough to provide the accurate information) while trustworthiness refers to a communicator's intent to transmit accurate information (i.e., communicator's quality of being honest and not being deceptive) (Priester & Petty, 2003). In other words, expertise is related to the perception of the source's capability while trustworthiness is related to the perception of the source's intentions.

Overall, high credibility sources are known to be typically more effective than low credibility sources (Pornpitakpan, 2004). However, findings regarding the extent to which the two dimensions account for source credibility are mixed: some (e.g., McGinnies & Ward, 1980) found that trustworthiness is more important than expertise, while others (e.g., Hovland & Weiss, 1951; Kelman & Hovland, 1953) found that trustworthiness was ineffective by itself or less important compared to expertise. This suggests that the expertise and trustworthiness dimensions of source credibility might have differential functions in persuasion.

Message credibility is defined as "the extent to which an audience believes a message" (Roberts, 2010, p. 45). It has also been defined as "an individual's judgement of the veracity of the content of communication" (Appelman & Sundar, 2016, p. 63). Message credibility is conceptually independent from source credibility, as non-source factors may affect credibility, such as medium, channel or message structure (e.g., Metzger, Flanagin, Eyal, Lemus, & Mccann, 2003). Metzger, Flanagin, and Medders (2010) explicated the difference between message credibility and source credibility and postulated that they are comparable to Aristotle's logos and ethos, respectively.

Although many scholars recognize message credibility as a distinct concept, empirical investigation of this domain does not seem to be as profound as that of source credibility. Appelman and Sundar (2016) explicated state of the art in this regard and listed previously identified 22 formative indicators related to message credibility. Though CFA (confirmatory factor analysis), they identified three subdimensions of message credibility: *accuracy*, *authenticity*, and *believability*.

The dual-processing theory perspective of credibility also suggest that message and source credibility should be treated as distinct constructs. Credibility has been frequently investigated in the context of persuasion (Pornpitakpan, 2004) using dual-processing models (e.g., Chaiken & Maheswaran, 1994; Chen, Duckworth, & Chaiken, 1999; Eagly, Wood, & Chaiken, 1978; Priester, Brinol, & Petty, 2009; Priester & Petty, 1995; Priester & Petty, 2003; Ratneshwar & Chaiken, 1991). Dual-processing theories such as HSM (heuristic-systematic model; Chaiken & Eagly, 1989) or ELM (elaboration-likelihood model;Petty & Cacioppo, 1986) contend that people go through information using two distinct processes (O'Keefe, 2013). Both HSM and ELM posit that humans have two distinct protocols for processing information, which are heuristic processing (or peripheral route) and systematic processing (or central route). Source attributes are thought to be related to heuristic or peripheral processing, while message attributes are thought to be related to systematic or central processing (Pornpitakpan, 2004). The two types of credibility are not only conceptually distinct under dual processing theories, but also have differentiating effects on persuasion. For instance, depending on different conditions regarding source credibility, receivers engage in issue-relevant thinking and pay a great deal of attention to the message, while in other occasions receivers will not allocate such scrutiny in processing the message (Priester et al., 2009). Earlier studies on machine journalism either did not distinguish the two different types of credibility or used only one of them without recognizing the other type of credibility. By recognizing the distinction between source and message credibility, this study includes the two as distinct types of credibility.

Credibility of news is expected to be a core variable related to perception of machine-generated news articles as it has been in earlier studies (e.g., Clerwall, 2014; Graefe et al., 2016; Waddell, 2018). This investigation proposes to examine message credibility and source credibility as distinct variables. According to dual-processing theories, source and message credibility have distinct roles, and capable of better explaining different outcomes of communication together. Thus, both source and message credibility are analyzed as separate constructs in this study.

Negative and Positive Information

Positive and negative information, or perceiving information as positive or negative, is known to affect our perception to the world differently. Tversky and Kahneman (1974; also in Tversky & Kahneman 1979), contended that positive and negative valence constructs need distinction, since negative and positive information and our reaction to them are related to different cognitive and behavioral outcomes. This is because the way we process loss and gain is different as well (Tversky & Kahneman, 1983). Specifically, due to illogical conclusions drawn from heuristics, people have different reactions to loss versus gain situations when mathematically the odds are the same (Tversky & Kahneman, 1974), yet neither positive nor negative appraisal of information has decidedly superior power in leading us to better decision making.

Results from research in communications also reported similar findings. Cacioppo and Gardner (1999) explicated the differentiating functions of positive and negative information. From an evolutionary psychology perspective, positive emotion provides people with a cue to explore the environment and maintain our attention at a constant level, and negative emotion and the bias towards it lets us calibrate our psychological stance so we can preserve ourselves (Cacioppo & Gardner, 1999). Lang et al. (2013) empirically tested this idea in a mediated communication context using LC4MP (limited capacity model of motivated mediated message processing; Lang, 2006). They found that both appetitive and aversive activation motivates our attention, and storing negative stimuli is more automatic.

The distinction between positive and negative constructs within credibility does not seem to exist in communication research. Research on credibility in media studies usually view credibility as a positive value ranging from low to high (e.g., Chaiken & Maheswaran, 1994; Petty & Cacioppo, 1986). Accordingly, source credibility, message credibility, and their subdimensions have been measured on a singular pane with adjective scales or using Likert-scales ranging from 0 and up.

Some researchers of *trust* asserted that trust and *distrust* are distinct concepts (e.g., McKnight & Chervany, 2001; McKnight & Choudhury, 2006; McKnight, Choudhury, & Kacmar, 2002). One of the most widely accepted definition for trust is “a person’s (the trustor) willingness to be vulnerable to another person (the trustee) on the basis that the trustee will act according to the trustor's confident expectations" (Mayer, Davis, & Schoorman, 1995, p. 712). Distrust is conceptualized as a reciprocal term for trust (albeit hypothesized as a distinct function) and defined as an expectation of injurious action, such that "the trustee will not act in the trustor's best interests" (Barber, 1983; as in Dimoka, 2010, P. 376). Lewicki, McAllister, and Bies (1998) also suggested that trust and distrust are distinct concepts, as trust is "confident, positive expectations regarding another's conduct," while distrust is "confident negative expectations regarding another's conduct." (p. 439).

Trust and distrust are frequently studied by having their dispositional variables to control for individual differences in trust and distrust (McKnight & Chervany, 2001; McKnight & Choudhury, 2006; McKnight, Kacmar, & Choudhury, 2004). Disposition to trust is defined as a tendency to be willing to depend on other people and be vulnerable to other people in general (McKnight et al., 2004). Disposition to trust has two subconcepts – *faith in humanity* and *trusting stance*. Faith in humanity refers to the assumption that people have on others in general, including benevolence, competence, and integrity (McKnight et al., 2004). Trusting stance is defined as a positional strategy that people apply regardless of the assumption that people in general have positive attributes (McKnight et al., 2004). Disposition to distrust is defined as "*the extent to which one displays a consistent tendency to not be willing to depend on general others across a broad spectrum of situations and persons"* (McKnight & Chervany, 2001). Disposition to distrust consists of two subconcepts. *Suspicion of humanity* refers to a tendency of a person to assume that general others are not usually benevolent, competent, or honest (McKnight & Chervany, 2001). *Distrusting stance* is defined as "*regardless of what one assumes about other people generally, one assumes that one will achieve better outcomes by dealing with people as though they are not well-meaning and reliable*" (McKnight & Chervany, 2001)

Dimoka (2010) explicated how distrust is discriminant from trust. First, discriminant validity between items of trust and distrust is established through statistical tests (McKnight & Chervany, 2001). This means that the measurements for trust and distrust are indexing two different psychological constructs. Second, trust and distrust elicit differential effects on other antecedent or consequential constructs (McKnight & Choudhury, 2006). For instance, Dimoka (2010) found that indicators of distrust had a stronger effect on decision making than cues for trust. Third, neuroimaging results on trust (Dimoka, 2010) found that trust and distrust are related to different regions of the brain, and these regions were activated at the same time in the context of online commerce.

The discriminant validity of distrust is important to communication research due the conceptual similarity between trust and source credibility. Some view the two are interchangeable (e.g., Fletcher & Park, 2017); trust as a close concept to medium credibility specifically (e.g., Kohring & Matthes, 2007), trust as a central concept to credibility along with other variables (e.g., Thorson et al., 2010); credibility as a precursor to trust (e.g., Shariff et al., 2017); credibility as sub-concept to trust (e.g., Dimoka, 2010). Source credibility and trust has been utilized together in a study (Lowry, Wilson, & Haig, 2014). The researchers of this study utilized source credibility to occur prior to trust, because source credibility more narrowly focuses on the attributes of the source which translates into "first impression" related to credibility and trust (Lowry et al., 2014).

The similarity between source credibility (e.g., Hovland & Weiss, 1951) and trust (e.g., Dimoka, 2010) seems to be that although the terminology for sub- and super-conceptualization may be flipped, they seem to direct towards very similar psychological phenomenon. Dimoka (2010) conceptualized trust (and distrust) as a construct that comprises of credibility (or discredibility) and benevolence (or malevolence). The key concepts for credibility (and discredibility) are competence (incompetence), honesty (dishonesty), and reliability (Gefen, 2002; McKnight & Chervany, 2001; Pavlou & Dimoka, 2006), and benevolence (and malevolence) was defined as trustor's belief on the trustee's commitment and motives towards the welfare of the trustor. Comparing this with aforementioned definitions and sub-concepts of credibility, both source credibility and trust consist of two sub-concepts - a judgment on the other's capability for the task (i.e., expertise and credibility), and judgment on the other's intention (i.e., trustworthiness and benevolence).

The conceptual closeness between trust and source credibility then leads to a question if negative credibility (or "discredibility") exists, as distrust has been identified to be distinct from trust. For instance, Priester and Petty (2003) found that with high trustworthiness (as a sub-concept of source credibility), people unthinkingly accept the information provided, but when trustworthiness is low, people do not necessarily reject the idea, but scrutinize the message then decide whether or not to accept the information. However, this finding does not warrant the existence of discredibility as it did not test discredibility as a distinct concept. But what if people find the trustworthiness to be negative, or in other words, perceive the sender's intention to be malicious?

In sum, as research on trust and distrust suggests that the two constructs are distinct, and trust and credibility are conceptually almost identical, it seems necessary to explore if discredibility is distinct from credibility. The conceptualization and measurement of trust and distrust in this study, which was developed mainly by McKnight et al. (2002), may provide additional advantage. The scale incorporates disposition to trust and distrust, which are measures for personal traits related to trust and distrust thus provides control for individual differences.

Source credibility measures that are typically employed in journalism thus far lack control for individual differences. By incorporating these measures, results of this study may deepen our understandings on trust and credibility in the context of journalism and communication.

In conclusion, if trust and distrust are distinct constructs that induce different effects on our cognition and behavior, credibility (as in Hovland & Weiss, 1951) and discredibility, as deeply related variables to trust, might as well be distinct constructs which result in different outcomes. Although there have been many studies that recognized the relationship between trust and credibility conceptually, and many agree that the two concepts are akin to each other, attempt to empirically investigate the relationship using statistical techniques such as factor analysis does not seem to exist in communication discipline. Thus, this study aims to investigate this domain, by investigating the relationship between trust and credibility at an operationalization dimension and exploring the possibility of the existence of "discredibility" as a discriminant concept compared to credibility through adopting operationalizations from trust literature.

Hostile Media Effect

Hostile media effect was first reported by Vallone, Ross, and Lepper (1985). When the researchers exposed their participants to a news article about Israeli-Palestinian conflict, they found an unexpected result – that the supporters for the two different groups (Israel and Palestine) perceived the news to be biased against their belief, when the news article was supposedly neutral. Since then, a number of studies (Arpan & Raney, 2003; Gunther, Miller, & Liebhart, 2009; Hansen & Kim, 2011; Huge & Glynn, 2010) were conducted on this topic for over decades using the term hostile media effect, interchangeably with hostile media perception or hostile media bias (Perloff, 2015).

Although creating perfectly neutral or objective news (or any information) is impossible, it is strikingly interesting that supporters of both sides view a news article on a controversial topic to be biased against them. That is, as Munno (2017) pointed out, the focus of hostile media bias is not about investigating biases in the news; rather, it is about investigating biases of audience members and its relationship to news perception.

Different definitions have been proposed for hostile media effect. Perloff (2015) explained that the consensus for the definition is a "*divergent perceptions of neutral, balanced, and evenhanded media content*." (p, 705, Perloff, 2015). There are complications in defining hostile media effect, such as whether or not to include partisanship or involvement as part of the definition. Perloff (2015) suggested that involvement could be considered as moderator for the effect so we can avoid conceptual and methodological complication, and defined hostile media effect as "*the tendency for individuals with a strong preexisting attitude on an issue to perceive that ostensibly neutral, even-handed media coverage of the topic is biased against their side and in favor of their antagonists' point of view* (p. 707)."

The effect of hostile media bias has been found in a range of contexts. Hansen and Kim (2011) reported that over 34 studies, their meta-analysis yielded a significant effect with an effect size of $r = .296$. The studies that were included in this meta-analysis included different types of medium (e.g., newspaper or television) and methods (i.e., experiment and survey), thus considering the variation of methodological settings among studies, Hansen and Kim (2011) concluded that a there is a reliable effect of hostile media bias.

The reason for which hostile media bias occurs have been explored. Perloff (2015) listed factors that were proposed as mediators: selective recall, which found to have no support (Giner-Sorolla & Chaiken, 1994); selective categorization, which was supported (Schmitt, Gunther, &

Liebhart, 2004); different standards was partially supported; and mixed results for prior media beliefs (Giner-Sorolla & Chaiken, 1994; Matheson & Dursun, 2001). Notably, Schmitt et al. (2004) investigated these three candidates for the reason why hostile media effects occur. The study found that the effect occurs most likely because of selective categorization over the others. That is, their findings suggest that hostile media effect occurs because "*opposing sides might attend to, process, and recall the same content in an article; however, each side tends to categorize the same aspects of a story differently - as contrary to their own position* (p. 625)*"*. This again supports the idea that hostile media effect is a biased perception resulting from the audience's perception of the news, rather than the bias within the news production.

Pertinent to the current investigation, involvement is identified as a moderating variable for hostile media effect (Hansen & Kim, 2010), as higher involvement was related to more hostile media effect, although significant effect was also observed in low involvement conditions. As aforementioned, involvement is not quintessential to the conceptualization of hostile media effect. However, because the participants of this study were randomly exposed to one of the three news topic conditions (explanation in detail in methods section), issue involvement was measured to control for the bias due to characteristics of the news topics.

The construct of involvement is known for its conceptual ambiguity (Roser, 1990; Salmon, 1986; Slater, 1997) due to different scholars conceptualizing it differently while using the same label. This problem exists as well for the conceptualization of involvement within hostile media effect literature (Choi et al., 2009).

This conceptual difference between scholars also exist in hostile media effects literature. *Issue involvement* refers to the extremity of a person's opinion (e.g., Christen & Gunther, 2003; Giner-Sorolla & Chaiken, 1994; Gunther & Christen, 2002), while *ego involvement* or *value-*

relevant involvement, which are conceptualized interchangeably (Choi et al., 2009), is defined as "the psychological state that is created by the activation of attitudes that are linked to important values" (Johnson & Eagly, 1989,p. 290).

Measuring issue involvement for a polarizing issue entails collecting two dimensions of information about participant's preexisting idea on the topic – the extremity of the preexisting idea (i.e., how far is a person's idea is from being neutral about the topic, as in Gunther & Christen, 2002); and the ideological direction of the preexisting idea (e.g., partisanship, or liberal versus conservative; as in Vraga & Tully, 2015). The current study employed three different news topics as stimuli to pursue external validity. The polarities of each topics were inherently not compatible to each other, thus only the extremity of issue involvement and perceived bias were employed to index hostile media effect, as in Choi, Yang, and Chang (2009).

Political ideology (i.e., political stance) on the other hand, was employed to control for bias in hostile media perception. Specifically, previous studies consistently find conservatives to perceive stronger hostile media bias than liberals (e.g., Eveland Jr & Shah, 2003; Feldman, 2011; Stalder, 2009). This is speculated to be due to the perception of U.S. news media having pro-Democratic bias (Lee, 2005). Alternately, this is also thought to be related to conservatives having a tendency to reject ambiguity (Jost, Jost, Glaser, Kruglanski, & Sulloway, 2003), which in case of hostile media effect, can be translated to rejecting ambiguous (i.e., neutral) information (Stalder, 2009). Understanding political ideology is important for hostile media effect research since political ideology is thought to moderate the relationship between hostile media effect and its subsequent constructs. For instance, political ideology is found to moderate the relationship between hostile media effect and activism(Feldman, Hart, Leiserowitz, Maibach, & Roser-Renouf, 2015). Specifically, they found that hostile media effect promotes activism for liberals while the effect is reversed for conservatives. Thus, understanding participant's political ideology is important for better understanding hostile media effect.

Hostile media effect is known to be related to news credibility (Gunther, 1988). Audiences who received a message are known to search for cues so they can infer potential causes for the message sender's position, including communicator attributes (e.g., personality traits; Eagly et al., 1978; Eagly, Wood, & Chaiken, 1981). Accordingly, Arpan and Raney (2003) found that news sources that are perceived as allies (thus more credible) induced less hostile media effect (i.e., perceived as less biased) in the context of sports journalism. Kim (2015) provides insight to the relationship between hostile media effect and credibility. Although Kim (2015) was not a hostile media effect study as it employed a stimuli that was intentionally biased, it found correlation between perceived bias and credibility.

On the other hand, other scholars found credibility judgements to be a result of hostile media effect (e.g., Vraga & Tully, 2015). This is based on theories that suggest *disconfirmation bias* (K. Edwards & Smith, 1996) or *biased assimilation* (Lord, Ross, & Lepper, 1979), where people tend to scrutinize information that is contrary to their belief and more likely to find the information to be weaker.

The two different approaches are incorporated in the theoretical model of the current investigation. Literature review on credibility revealed that source credibility and message credibility are distinct constructs that are related to discrete components of communication. Because source credibility is thought to be peripheral or heuristic processing, which takes relatively less time and cognitive effort thus occurs quicker; and message credibility is thought to be a central or systematic processing, which takes more cognitive effort and time thus occurs slower. Earlier studies frequently utilized this temporal difference between source and message credibility to better understand how the two works with each other in persuasive messages (e.g., Priester & Petty, 2003). Because source credibility theoretically occurs immediately, it should occur prior to hostile media effect; and because message credibility is a result of the audience's systematic investigation of the entire communication, perceived bias (i.e., hostile media effect, in case the message is fairly neutral) would affect message credibility. Thus, source crediblity temporally precedes message credibility, and hostile media effect may occur at some point between source credibility and message credibility. This means that hostile media effect may be a process of rationalization by audience, thus possibly a mediator for the relationship between source and message credibility.

In addition, hostile media effect investigates mostly the negative domain of credibility or in other words how credibility can be undermined. However, investigation that focuses primarily on the negative part of credibility has not been conducted. Thus, by separating distrust as a divergent variable compared to credibility, the relationship between hostile media effect and news credibility (and discredibility) may be better explained.

Fake News and Credibility

The phenomenon of "fake news" is one of the prevalently used terms in recent years in relation to the credibility of news. 2017 report from Reuters (Newman, Fletcher, Kalogeropoulos, Levy, & Nielsen, 2017) recognized fake news as one of the threats to news industry as it undermines the public's trust in news media. Lazer et al. (2018) also remarked the importance of multidisciplinary effort on solving the issues regarding fake news, especially in the age of historically low trust and credibility of public on news organizations.

Tandoc et al. (2018) reviewed the current state of scholarly definitions of fake news, and identified news satire, news parody, news fabrication, photo manipulation, advertising, public relations, and propaganda as possible typologies of a broad definition of fake news. Lazer et al. (2018) defines fake news as "fabricated information that mimics news media content in form but not in organizational process or intent (p. 1094)." Allcott and Gentzkow (2017) defines fake news as "news articles that are intentionally and verifiably false, and could mislead readers" (p. 213). Shu, Sliva, Wang, Tang, and Liu (2017) defines fake news as a news article that lacks authenticity in information with an intention to mislead. As Tandoc et al. (2018) noted, the definitions thus far commonly recognize two dimensions in fake news: *facticity* and *intention.* Here, facticity is defined as "the degree to which fake news relies on facts," and intention refers to "the degree to which the creator of fake news intends to mislead" (Tandoc et al., 2018, p. 147).

Tandoc et al. (2018) also noted that the role of audience is rather underrated. They suggested that fake news remains as a work of fiction in case the audience is not deceived. Accordingly, an investigation on the authentication process of audience upon receiving news has been conducted (Tandoc et al., 2017). This suggests that production of fake news and audience's judgment of fake news are independent events. This then suggests that understanding the sociopolitical impact of fake news could be also related to the psychological mechanism of how people make judgments about fake news.

Thus, production of fake news becomes pointless when an audience recognizes its malintent and lack of facticity. However, this authentication process that is required for audiences to make sure that they are not deceived could be a rigorous and challenging process. The ability to validate information from news can be hindered due to many reasons –common mistakes, low motivation, lack of means to verify, or even refuse to accept the information at hand and reject it by calling it fake, which would lead to judging an authentic piece of information to be fake. For instance, it would be hard for an audience who supports unrestricted gun ownership to perceive a news article on gun control to be fact-based and with good intentions, because of their lack of motivation to intake the information. Rather, it would be easier for the audience to reject the information altogether by claiming it to be “fake,” which may function as a rationalization for their decision. In other words, because rigorous “fact checking” would be a systematic process which require significant cognitive effort, there is a possibility that people will resort to an easier, heuristic process. This means that people in this study would be relying on their perceived credibility of the message and source, or perceived bias to make judgment of fake news.

And finally, as we focus on the perception of fake news rather than the production of it, the concept becomes more compatible to other perceptual variables of news, mainly news credibility. Furthermore, this also suggests that the credibility of fake news may not mean a lack of credibility, but rather negative vector of credibility.

Research Questions and Hypotheses

With the current state of literature reviewed in this section, the current study proposes the following research questions.

A line of studies on machine journalism has found that credibility may differ when people believe that the article was written by a machine rather than a human journalist. This leads to a question of how and why people perceive machines as a different type of social actor. While CASA supports the idea that reaction towards machines can be fathomed through social psychology theories and measures, the results from previous machine journalism studies suggest that there is apparent difference in these reactions. This study proposes that people not only react towards machines as if they are social actors, but also have different schemas for machines compared to that for humans. This study intends to see if the previous results on machine versus human journalism can be further explained by difference in a specific sub-concept of credibility and trust.

To find if people differently react to journalistic work done by artificial intelligence compared to that of humans, the current study focuses on the difference in terms of credibility and trust. This investigation differs from previous research in that it employs a more controversial news topic as stimuli. Specifically, the current study attempts to approach the concept of credibility more systematically by measuring source credibility, message credibility, trust, and distrust distinctively. Since there is no existing measure for discredibility as a distinct construct, distrust is employed as a measure of negative perception of trust/credibility.

While previous studies on machine journalism investigated the effect of data-driven news articles, this study investigates if news articles that involve controversial issues are perceived differently in terms of credibility, trust, and distrust. Because previous machine journalism studies have contradicting results (Clerwall, 2014; Graefe et al., 2016; Liu & Wei, 2018; van der Kaa & Krahmer, 2014; Waddell, 2018; Zheng et al., 2018), the effect of journalist condition (machine versus human journalist) on credibility, trust, and distrust is explored as a research question rather than having a directional prediction. Thus:

RQ1. What is the effect of machine versus human journalist on the credibility, trust, distrust for a news article with a controversial topic?

Literature from other disciplines suggest that trust and distrust are distinct concepts. Previous research on source credibility on the other hand seems to have been focused on positive credibility only. Considering that trust and credibility are closely related, credibility might as well have its counterpart. Thus:

RQ2. Is distrust distinct from source/message credibility?

Source credibility and trust are conceptually close or interchangeable to each other according to past studies. However, there is a gap in literature in terms of empirically testing the relationship between the two constructs. The current study attempts to empirically test the relationships between indicators of trust (McKnight et al., 2002) and source credibility (Bhattacherjee & Sanford, 2006). Thus, it is hypothesized that:

H1a: Source credibility and trust will fail to exhibit discriminant validity in journalism context.

H1b: Source credibility and distrust exhibit discriminant validity in journalism context.

Hypotheses H3 to H7 were tested using a partial least square modelling. Specifically, this study investigates the relationship between hostile media effect, credibility, trust, distrust, and fake news.).

RQ3. What is the relationship between source/message credibility/discredibility and hostile media effect?

The three news topics were about government policies that are potentially controversial. Thus, political ideology was measured to control for individual differences in participants' political stance. Having more conservative political stance is found to be related to less trust or credibility for journalism (e.g. Lee, 2010). Thus:

H2a: Having more conservative political stance predicts higher source credibility or trust.

H2b: Having more conservative political stance predicts higher distrust.

Two constructs that lack discriminant validity should not be included in a single model. Because H1a predicts lack of discriminant validity between source credibility and trust, H2c is included in the model if H1a is not supported. Figure 1 demonstrates the theoretical model in case H1a is supported. Figure 2 demonstrates the theoretical model if H1a is not supported, thus with both trust and source credibility in the model. As a "first impression" measure, source credibility predicts trust as in Lowry et al. (2014):

H2c: Source credibility is positively related to trust.

Literature suggest that conservatives are more likely to perceive media to be hostile against their thoughts (Feldman, 2011; Feldman et al., 2015; Lee, 2005). Thus:

H3: More conservative political stance predicts higher hostile media effect.

Perloff (2015) speculated credibility may be related to hostile media effect. While source credibility is known to be a fast and heuristic reaction, message credibility is thought as a systematic reaction which takes place slowly. Thus, while source credibility, trust, and distrust affect hostile media effect, hostile media effect affects media credibility:

H4a: Source credibility or trust predicts lower hostile media effect.

H4b: Distrust predicts higher hostile media effect.

H5: Hostile media effect predicts lower message credibility.

Because hostile media bias and lower media credibility would lead to not believing the information within a news article, hostile media effect and media credibility will be related to perception of fake news:

H6: Hostile media effect positively predicts perception of fake news.

H7: Fake news and media credibility are negatively related.

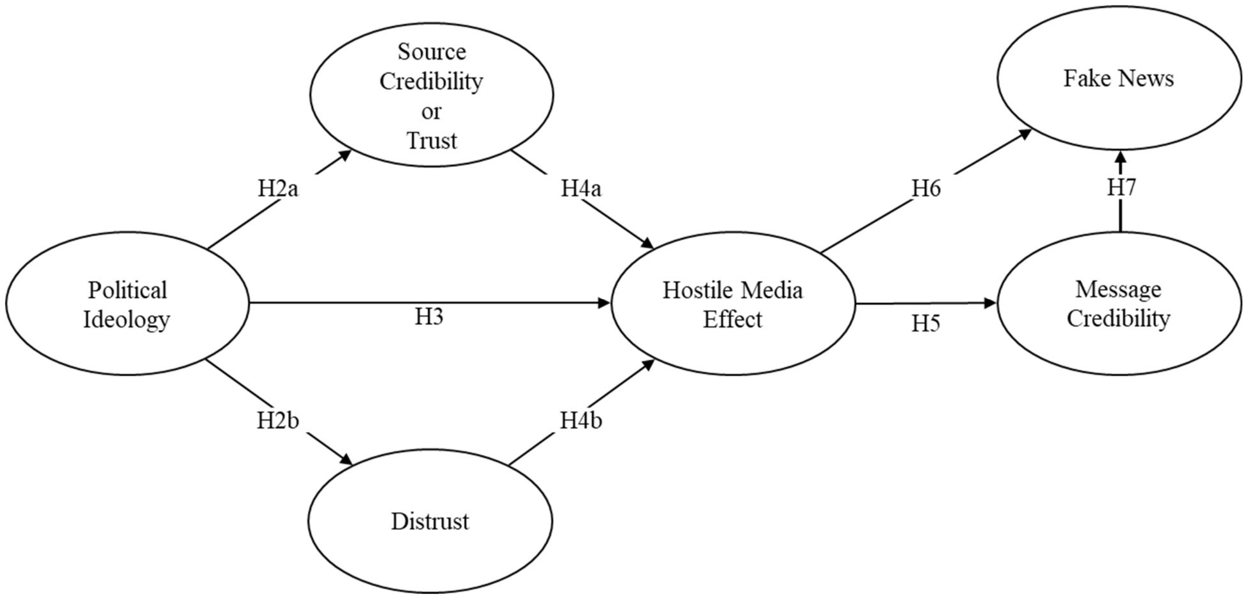

Figure 1. Theoretical model, H1a supported

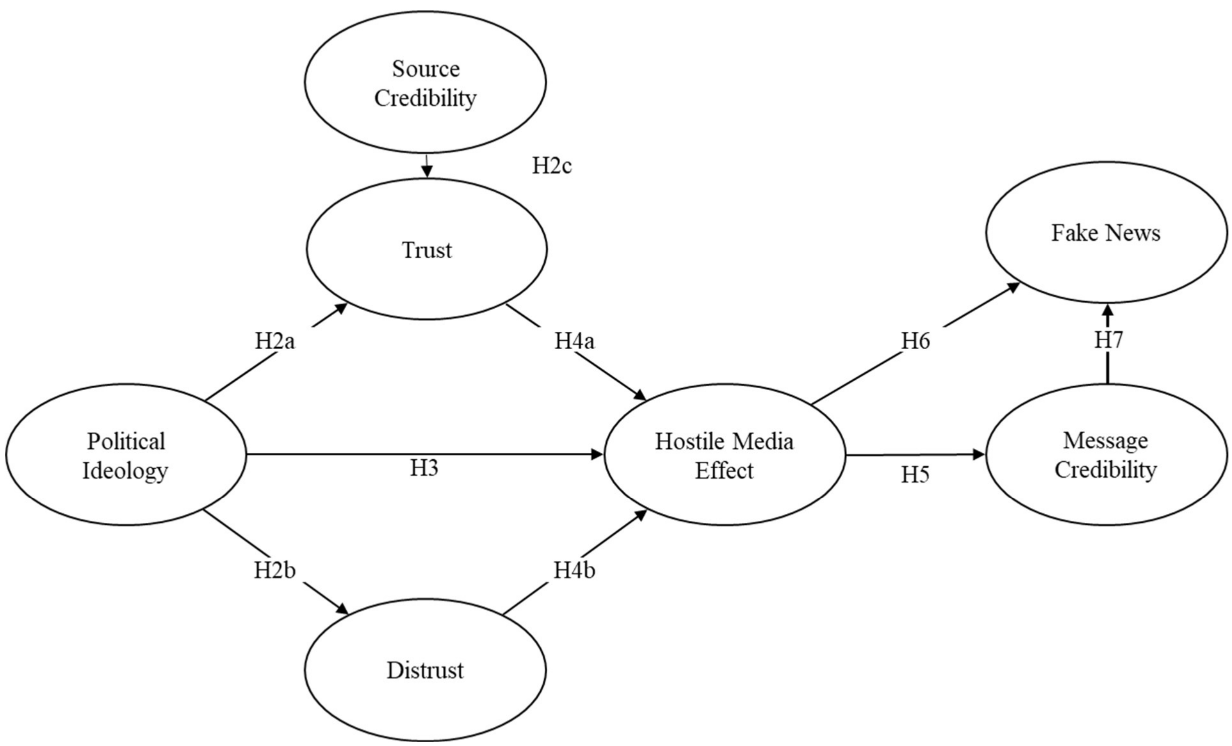

Figure 2. Theoretical model, H1a not supported

Chapter 3: Method

A 2 (journalist: human journalist vs. machine journalism) x 3 (news topics: gun legislation vs. immigration policy vs. environment policy) between-subjects factorial design experiment was conducted to test the hypotheses in this study. The first between-subject factor was journalist (human or machine), and the second between-subject factor was news topic. 3 news articles (gun control/rights, more jobs vs. environment, and immigration issues) were used to pursue better ecological validity as recommended by O'Keefe (2004). In other words, although news topic condition was implemented, this factor was not intended for hypothesis testing or solving research questions. In an effort to overcome the inevitable variance in dependent variables due to news topic condition, dispositional variables, disposition to trust, disposition to distrust, political ideology, and issue involvement were measured. Post-exposure questionnaire included credibility scales, trust/distrust scales, perception of bias questions, and perception of fake news items.

Participants

A total of 652 individuals were recruited as participants for this study and given monetary compensation for their participation. The sample size was proposed by following precedent studies and guidelines: PLS-SEM (partial least squares structural equation modeling) provides room for bootstrapping and requires smaller sample size (Hair, Ringle, & Sarstedt, 2011) especially when compared to the more conventional SEM (i.e., CB-SEM; covariance based structural equation modeling). By using PLS-SEM, McKnight and Choudhury (2006) investigated trust and distrust measures by recruiting 571 participants in their study. Darke and Ritchie (2007) investigated the effect of trust and distrust in advertisement by employing dual-processing theories. In their 2 x 2 x 2 design, they had 165 participants. The rule of thumb for choosing PLS-SEM over the more conventional type of SEM is when the study design is to identify key driver constructs; is exploratory or an extension of an existing structural theory; includes complex structural model; and when the sample size is relatively low or the data are nonnormal (Hair, Ringle, et al., 2011). Hoe (2008) suggested that the general rule for ideal sample size for employing structural equation modeling is to have at least 200 subjects, or 10 subjects per connections. Thus, the number of participants were proposed as 600.

Recruitment of participants and consequent web experiment was conducted via Prolific, which are known to yield more reliable results compared to Amazon M-turk (Palan & Schitter, 2018). A total of 652 participants participated in this study. Among the participants, 52 were participants in pilot studies. Pilot study data was merged with main data since pilot study did not find any glaring issue with experiment design. Participants with problematic responses were excluded: those who did not pass the attention check measure ($N = 147$), those with duplicate participations ($N = 8$), or those with unreliable answers ($N = 1$; e.g., answering 3 throughout the whole survey) were excluded. Additionally, because hostile media effect is rooted from a preexisting bias of the reader, hostile media effect is predicted to not occur when the reader is unbiased on a given topic (Choi et al., 2009). Thus, participants that appeared to have no bias on the issue (i.e., those who answered 4 = "neutral" for issue involvement items) was excluded from the analysis ($N = 96$) by following previous studies on hostile media effect (Choi et al., 2009). Specifically, the number of participants that were excluded from the analysis due to having unbiased opinion for each topic was 10 for gun legislation condition, 54 for immigration policy condition, and 32 for environment policy condition. Issue involvement, instead of political ideology, was used here to exclude cases that had neutral stance for several reasons: (1) issue involvement and political ideology was not correlated ($p = .527$); (2) while political ideology is an indirect indicator that may predict participant's bias against specific issues, issue involvement is a more direct measure that indicates participants having preexisting bias to an issue regardless of their political stance; (4) and theoretically the inclusion of political ideology was to control for conservatives reporting more hostile media bias compared to liberals, rather than to anchor participant's preexisting attitudes for examining hostile media bias itself.

After excluding these participants, the sample size used for the analyses were 400. The sample consisted of 175 males (43.75%), 220 females (55%), 3 who identified as "other," (0.75%), and 2 who decided not to share (0.5%); 339 White/Caucasian (84.75%), 30 Black/African American (7.5%), 27 Hispanic (6.75%), 27 Asian (6.75%), and 6 Native American/Alaska Native (1.5%); age ranged from 19 to 80, with a the mean age of 36.34 (*SD* = 13.81). Regarding participants' political party affiliation, there were 65 Republicans (16.25%), 205 Democrats (51.25%), 113 Independent (28.25%), 12 who identified as "other" (3%), and 5 who decided not to disclose (1.25%).

Procedure

Participants were recruited using Prolific, an internet-based participant recruitment platform. The entire procedure took place online. First, the participants were asked if they agreed to the terms of the consent form. Then, participants completed a set of questions before stimuli exposure. Here, participants were asked of their demographic information, involvement with each news topic, and disposition to trust and distrust. Then, the participants were randomly assigned to one of the six news article conditions, which consisted of two levels of journalist (human vs. machine) and three different topics (gun legislation vs. immigration policy vs. environment policy) conditions. Information about participants in each group is demonstrated in Table 2. After the exposure to the stimuli, participants were asked to finish the post-survey. The post exposure survey consisted of questions regarding perceived bias, source credibility, message credibility, trust, distrust, and perception of fake news. This investigation intended to provide a monetary compensation of $6.50 per hour for each participation. The estimated time to complete all the tasks in this study was 20 minutes according to the tools provided by Qualtrics. Considering that this estimation from Qualtrics assumes general public as participants, and participants from Prolific are more proficient, Prolific participants were expected to take less than 20 minutes to finish all the tasks within this study. Still, since dispensing compensation less than promised is undesirable, the estimated time to finish participation was more generously set as 25 minutes. Thus, the actual payment for participation was $2.71, which meant that participants was paid $6.51 per hour if they finished in 25 minutes. As a result, Prolific reported that participants were effectively compensated in the amount of $9.04 per hour, meaning that average completion time for participants was approximately 18 minutes on average.

Materials

Stimuli presentation. A total of three news articles were used in this study. Each participant was randomly exposed to one of the three news articles. The three articles were on gun control versus gun rights (i.e., gun legislation), opening border for refugee assimilation (immigration policy), and prioritizing economy vs. environment (environment policy). The topics of the stimuli were selected based on report from Pew Research Center (2018), where they found that the three topics were highly polarizing. Approximately half the population supported each side of the controversies. The original articles were taken from Groppe (2019), Colvin (2019), and Rich and Broder (2011), respectively.

The three stories were modified so that equal portion of the article was spent covering interviews or opinions from each side of the controversy; and the length of the three articles were about one-page, single spaced. The length of the body of each article was 345 (gun legislation), 476 (immigration policy), and 423-word long (environment policy). The stories were presented in simple text, following a headline which was also in simple text. No other information (e.g., media organization) was provided. The stimuli are demonstrated in Appendix B.

Journalist manipulation. The first factor, whether the source was a machine, a human, manipulated by stating the source on the top left of the news article. The source will be printed as "The information in this article was gathered and written by a human (artificial intelligence) journalist" for machine and human journalism condition.

Measures

Testing the reliability of constructs is essential to establishing model validity for PLS-SEM. To avoid redundancy, Cronbach's alpha and composite reliability (CR) are reported under "Data Validation for PLS-SEM" in the results section instead of the methods section.

Manipulation Check. In order to check the effectiveness of manipulation, a single question directly asked if participants could correctly recall the writer ("a machine algorithm" or "a human journalist") for the news article correctly.

Demographic measures. Participant's age, education, ethnicity, gender, political affiliation, political ideology, and yearly income was directly asked. A participant's political ideology was measured using a 1-item, 7-point Likert-type scale (1 = "extremely liberal" – 7 = "extremely conservative").

Issue involvement. A set of questions related to participant's preexisting positions on the news topics were asked by modifying issue involvement items in Christen and Gunther (2003). Three questions were asked per news topics – with three news topics in this study, together there were nine questions that were asked for issue involvement. All participants, regardless of their randomized group assignments, were asked to answer all nine questions.

The first two questions for each topic asked the extent to which participants supported each side of the polarizing issue (e.g., “I am a strong supporter of gun control” and “I am a strong supporter of gun rights”) using 7-point Likert-type scale (1 = “strongly disagree” – 7 = “strongly agree”). The third question for each topic asked participant’s position on each topic (e.g., “If I had to choose between the two policies, I would support:”) and answered using 7-point scale (e.g., 1 = “gun rights” – 7 = “gun control”).

The direction of preexisting opinion on the topic was omitted and only the extremity of the involvement was operationalized through data manipulation. First, the scores for issue involvement were normalized so it ranged from -3 to 3 with 0 being neutral. Then, the scores for issue involvement were transformed into absolute values. As a result of this transformation, issue involvement ranged from 0 to 3, with 0 being neutral and 3 being having a strong opinion. Higher scores in issue involvement meant that the participant had extreme opinion that is far from being neutral, regardless of their direction of opinion.

Perceived bias. A total of two perceived bias questions that measured selective recall and perceived bias was adopted from Schmitt et al. (2004) to assess hostile media effect. Two items asked if the message was biased towards supporters, and if the message was biased towards opponents; with 11-point scale (1 = “strongly biased against” to 11 = “strongly biased in favor”; with a middle ground of 6 = “neutral”).

Hostile media effect index. Although hostile media effect is observed by simply finding negative relationship between issue involvement and perceived bias (e.g., Gunther et al., 2001), a standalone index was created so the relationship between hostile media effect and its possible antecedents and consequences could be easily explored.

By following Choi et al. (2009), hostile media effect index (i.e., HME index) and issue involvement scores were transformed so they convey only the extremity of the idea. The raw scores of the items for issue involvement and perceived bias were normalized so that they ranged from -3 to 3 with 0 being neutral. Then, the composite variable of perceived bias and issue involvement were created using its respective items. Next, hostile media effect index was created by subtracting perceived bias scores from issue involvement scores; and reverse coding the hostile media effect index scores for the cases that had issue involvement scores that were smaller than 0. This resulted in creating a stand-alone hostile media effect index (i.e., HME index). The score for HME index theoretically was larger than -3 and smaller than or equal to 6, with closer to -3 being strongly congenial and 6 being strongly biased against the participant's opinion on the topic (i.e., stronger hostile media effect). HME index actually ranged from -2.67 to 6, with $M = 1.54$, $SD = 1.28$).

As a result, higher scores in HME index indicated higher perceived hostile bias (i.e., article was biased against the participant's idea), regardless of the direction of the bias.

Trust and distrust measures. A 20-item, 7-point Likert-type scale (1 = "strongly disagree" – 7 = "strongly agree"). of trust and distrust measure from Moody, Galletta, and Lowry (2014), which were originally developed by McKnight et al. (2002) was modified to fit journalism context. This set comprises of subsets of items for benevolence (3 items), competence (4 items), integrity (4 items), malevolence (3 items), incompetence (3 items), and deceit (3 items).

A 25-item disposition to trust and distrust (i.e., trait measures of trust and distrust) measures imported from Moody et al. (2014) were also modified and used in this study in the pre-survey. Disposition measures comprised of benevolence (3 items), competence (3 items), integrity (3 items), trusting stance (3 items), malevolence (3 items), incompetence (3 items), deceit (3 items), distrusting stance (4 items).

Credibility measures. A 4-item source credibility measure that was typical to media research was adopted from Bhattacherjee and Sanford (2006). Answers for these items were collected using 7-point Likert-type scale (1 = "strongly disagree" – 7 = "strongly agree").

Message credibility measure was adopted from Appelman and Sundar (2016) by using three adjectives (accurate, authentic, believable) followed by a question ("How well do the following adjectives describe the content you just read?") on a 9-point Likert-type scale (1 = "strongly disagree" – 9 = "strongly agree").

Fake news. Perception of fake news was created in this study by incorporating theoretical definitions of fake news from Tandoc et al. (2018), which identified two components that defined fake news: reliance on facts and intention to mislead. Total of four items were used to assess perception of fake news. Two questions directly asked how much they felt the news was fake or true; one item asked if the news article relied on facts; and the last item asked if participants thought the writer intends to mislead. Answers for these items were collected using 7-point Likert-type scale (1 = "strongly disagree" – 7 = "strongly agree").

Source attribution. A question asked source attribution, the extent to which a participant believed that the article was written by either a machine journalist ("The article that I read was written by a machine algorithm journalist") using 7-point Likert-type scale (1 = "strongly disagree" – 7 = "strongly agree").

Political Ideology. A single question asked if participants viewed themselves as liberal or conservative, using an 7 point Likert-scale with 1 being "liberal" and 7 being "conservative."

The actual survey questions in this study are attached in Appendix A.

Chapter 4: Results

Initial Data Analysis

A series of analyses were conducted to understand the relationship between experiment condition in terms of the main variables. Listwise deletion was used throughout all statistical analyses in this study.

A series of ANOVAs and an ANCOVA were conducted for experimental conditions. Composite variables for source credibility, trust, distrust, disposition to trust, disposition to distrust, message credibility, perception and hostile media index were created. Most constructs had acceptable Cronbach's alpha larger than .70, as in Table 28. Shapiro-Wilk test of normality was conducted to assess sample distribution. Here, as in Table 3, the result of Shapiro-Wilk test was significant for the dependent variables mentioned above, suggesting violation of normal distribution. However, as Hoyle (1995) pointed out, Shapiro-Wilk test for larger samples ($N > 300$) is known to be less reliable since larger sample size may lead to the test being too sensitive to minute differences (i.e., type I error). Therefore, skewness and kurtosis for each variable was inspected. The result in Table 3 shows that skewness and kurtosis for the variables were all within acceptable range (i.e., between -1 and 1). Thus, the following tests were conducted under the assumption of normal distribution.

While journalist condition was a manipulation, topic of the article was varied to pursue more generalizable results. Because RQ1 investigates the effect of journalist condition on credibility and trust, the focus of the preliminary data analysis was not on the effect of journalist condition but on the effect of topic of the article, but to investigate if there was any unintended effect from it. The following two-way ANOVAs and ANCOVAs all had journalist and article topic as condition variables.

A series of ANOVAs and ANCOVAs were conducted to verify that there was no effect of topic on dependent variables. A two-way ANOVA tested for the effect of journalist condition and news topic on source credibility. The result for this test is demonstrated in Table 4 and 5. The result revealed no main effect of article topic; $F(2, 393) = 0.44$, $p = .646$, $\eta_p{}^2 < .01$, journalist; $F(1, 393) = 1.19$, $p = .277$, $\eta_p{}^2 < .01$, or interaction; $F(2, 393) = .08$, $p = .923$, $\eta_p{}^2 = .01$. A two-way ANOVA with message credibility as criterion and journalist condition and news topic condition as factors revealed a significant main effect of journalist condition with medium effect size; $F(1, 394) = 4.60$, $p = .033$, $\eta_p{}^2 = .01$, but not for news topic condition; $F(2, 394) = 2.84$, $p = .060$, $\eta_p{}^2 = .01$ or interaction; $F(2, 394) = 0.18$, $p = .837$, $\eta_p{}^2 < .01$. The result for this test is described in Table 6 and Table 7. The effect of journalist condition on message credibility is discussed in detail later reported with results for RQ2. The two-way ANCOVA for trust with disposition to trust as covariate and journalist condition and news topic as factors revealed no main effect of article topic; $F(2, 393) = .654$, $p = .520$. The result for this analysis is shown in Table 8 and Table 9. Journalist manipulation had a significant effect; $F(1, 393) = 10.198$, $p = .002$, which is also discussed later with RQ1 results. There was no significant main effect from interaction; $F(2, 393) = .571$, $p = .565$. The two-way ANCOVA for distrust with disposition to distrust revealed no main effect of article topic; $F(2, 393) = .323$, $p = .462$, journalist condition; $F(1, 393) = .\ 543$, $p = .462$, or interaction; $F(2, 393) = .930$, $p = .396$. The result for this analysis is demonstrated in Table 10 and Table 11. Thus, it was concluded that topic did not have significant effect on credibility and trust. This was as expected, because the intention of employing three different topics in the design was to pursue generalizability of the results.

A series of two-way ANOVAs were conducted to test effects of journalist condition and news topic on hostile media effects constructs, which were issue involvement, and hostile media effect. News topic had a significant main effect on issue involvement with a strong effect size; $F(2, 394) = 57.36$, $p < .001$, $\eta_p^2 = .23$, no significant main effect of journalist condition; $F(1, 394) = 0.64$, $p = .425$, $\eta_p^2 < .01$, or interaction; $F(2, 394) = 0.09$, $p = .917$, $\eta_p^2 < .01$. The result for this analysis is in Table 12. Main effects analysis revealed that participants had a significantly more extreme ideas on gun policy compared to environment policy ($\Delta = .283$, $p = .005$); gun policy compared to immigrant policy ($\Delta = 0.958$, $p < .001$); and environment policy compared to immigration policy ($\Delta = 0.675$, $p < .001$). This result is shown in Table 13. News topic had significant main effect on hostile media effect as well, again with large effect size; $F(2, 394) = 35.10$, $p < .001$, $\eta_p^2 = .15$, with no significant effect of journalist condition; $F(1, 394) = .16$, $p = .692$, $\eta_p^2 < .01$, or interaction; $F(2, 394) = .82$, $p = .439$, $\eta_p^2 < .01$. Main effect analysis showed that people perceived the immigration policy article to be more biased compared to gun policy article ($\Delta = -1.024$, $p < .001$), or environmental policy article ($\Delta = -1.082$, $p < .001$). Difference between gun article and environment article were not significant ($\Delta = -0.058$, $p < .916$). The result for this analysis is described in Table 14 and 15.

Because previous studies (e.g., Lee, 2005) on hostile media effect found that conservatives are more likely to find media as biased against their beliefs, the relationship between political ideology and hostile media effect was explored. First, a one-way ANOVA with political ideology as criterion and news topic as factor (Table 16 and 17) revealed that the main effect of news topic was not significant, $F(2, 393) = 0.65$, $p = .521$, $\eta_p^2 < .01$. A regression analysis was used to test if the political ideology significantly predicted participants' hostile media effect index (Table 18). The result indicated weak but significant relationship ($R^2 = .01$, $F(1,394) = 4.73$, $\beta = .05$, $p = .03$) between political ideology and hostile media effect. Next, one-way ANCOVA was conducted to see if controlling for political ideology altered the effect of news topic on hostile media effect index. The one-way ANCOVA result for hostile media index with political ideology as covariate and news topic as factor revealed that the effect of article topic was significant; $F(2, 392) = 22.77$, $p < .001$ (Table 19). The comparison of estimated means (Table 20) showed that hostile media effect was significantly lower for immigration news article topic ($M = .90$, 95% CI [.70, 1.10]) compared to gun ($M = 1.84$, 95% CI [1.65, 2.04]) or environment ($M = 1.90$, 95% CI [1.71, 2.09]) topics.

A two-way ANOVA using age as independent variable (Table 21 and 22) revealed no main effect of article topic; $F(2, 394) = 0.63$, $p = .534$, $\eta_p^{2} < .001$, journalist; $F(1, 394) = 1.68$, $p = .195$, $\eta_p^{2} < .001$, or interaction; $F(2, 394) = 1.55$, $p = .214$, $\eta_p^{2} < .001$, suggesting that there were no difference in terms of age between groups. A one-way ANOVA that tested the effect of gender on hostile media effect to see if the result replicated earlier findings (e.g., Gunther & Schmitt, 2004). The result (Table 23 and 24) revealed that there was no effect of gender on hostile media effect: $F(1, 398) = 1.00$, $p = .317$, $\eta_p^{2} < .01$.

The result from preliminary analysis suggests that there is difference in terms of issue involvement and hostile media effect depending on news topics. The difference between news topics in terms of hostile media effect was not intended. This result, however, did not suggest any violation of assumptions for PLS-SEM. Therefore, hostile media effect was further tested using PLS models.

Effect of Machine Journalism on Credibility, Trust, and Distrust

RQ1 questioned if credibility, trust and distrust perception would be different for machine journalism condition. A series of t-tests were conducted to test RQ1. The result from t-test shows that there is no difference in terms of source credibility; $t(397) = -1.093$, $p = .275$, $\Delta = -0.130$. Message credibility was significantly higher on humans with small effect size (M =

6.922) versus machines (M = 6.556); t(398) = 2.139, p = . 033, Δ = 0.366. Trust was significantly higher for the human journalist condition (M = 4.798, SD = .964) than for the machine journalism condition but with small effect size (M = 4.486, SD = .942); t(398) = 3.273, p = .001, Δ = 0.312. There was no group difference in terms of distrust; t(398) = .008, p = .935, Δ = -0.02. Parameters for t-tests are demonstrated in table 25; and means and standard deviations for t-tests are demonstrated in Table 26.

Sub-components for trust (benevolence, competence, and integrity) and distrust (malevolence, incompetence, and deceit) were further investigated to explore if a specific sub-concept accounted for the result above. Human journalists received higher scores on sub-concepts of trust: benevolence with small effect sizes; t(398) = 4.158, p < .001, Δ = 0.470, competence; t(398) = 2.070, p = .039, Δ = 0.242, and integrity; t(398) = 2.354, p = .019, Δ = 0.224. Among the sub-concepts of distrust, only incompetence; t(398) = 2.133, p = .033, Δ = 0.276, was significantly higher albeit small effect size for machine journalism condition compared to the human journalist condition. Other sub-concepts of distrust was not significantly different between groups: malevolence; t(398) = -.850, p = .396, Δ = -0.100, deceit; t(398) = -1.362, p = .174, Δ = -0.178. The results from these analyses are demonstrated in Table 25 and 26.

Discriminant Validity Between Credibility and Trust Variables

H1 predicted discriminant validity between credibility and trust measurement items. Before testing discriminant and convergent validity, exploratory factor analysis (EFA) was conducted to investigate to get a general idea of how latent constructs aligned with each other. By following recommendation by Segars (1997), factor loadings were examined first through EFA, then discriminant validity test by comparing correlation and the square root of average variance extracted (AVE) was conducted to analyze the discriminant validity between constructs. Items for latent constructs of benevolence (three items), competence (four items), and integrity (four items) which consisted trust; malevolence (three items), incompetence (three items), and deceit (three items) which consisted distrust; source credibility (four items); and message credibility (three items) were included in the analyses.

Exploratory factor analysis. First, EFA was conducted. Although EFA does not provide an explicit test for unidimensionality and the factor solution from EFA result is one of an infinite number of solutions, it provides a general idea of the dimensionality of items (Segars, 1997). Varimax rotation assumes that the factors are completely uncorrelated, oblique rotation assumes that factors are correlated (Brown, 2009). Although trust and source credibility measures theoretically should be correlated the correlation coefficients between these constructs were tested. The correlation between items here are demonstrated in Table 37. Because of the significant correlations for the items between trust, distrust, source credibility, and message credibility, oblique rotation were significant, oblique rotation was used for all EFAs conducted in this study.

With all aforementioned items included, the scree plot for eigen values from parallel analysis suggested using 5 factors. The result in Table 27 demonstrates the factor loadings of items on five factors. Factor 1 had loadings from malevolence and deceit items and explained 16% of the total variance; factor 2 was competence and incompetence, which explained 15% of the variance; factor 3 was benevolence, and explained 12% of the total variance; factor 4 was source credibility, and explained 12% of the variance; and factor 5 was message credibility, which explained 11% of the total variance. Together, the five factors explained 66% of the total variance.

Items for competence and incompetence did not show overall low factor loading, and malevolence and deceit items were loaded on factor 2 together. Notably, discrete loadings for trustworthiness and expertise items under source credibility were not observed, suggesting that source credibility is unidimensional. These factor loadings that contradicted theoretical conceptualizations were of interest in later analyses.

Discriminant validity testing. Discriminant validity was examined by comparing the square root of AVE and correlation. AVE is known to be a good indicator to assess both convergent validity and discriminant validity in that AVE should be higher than .5 (Bagozzi & Yi, 1988) for convergent validity, and the square root of AVE for each latent construct should be larger than correlation coefficients that includes each latent construct (Fornell & Larcker, 1981). This means that if the square root of AVE is smaller than the correlation coefficients, items of a construct explains variance of the other construct, as much as it does for the target construct (Zaiţ & Bertea, 2011).

As reviewed theory section, credibility and trust are close but may be distinct constructs. The result in Table 37 shows that some pairs of constructs lacked discriminant validity: correlation between integrity and source credibility (.777) was higher than square root of AVE for integrity (.765); correlation between integrity and benevolence (.823) was higher than square root of Ave for integrity (.765) and benevolence (.801); and correlation between malevolence and deceit (.934) was higher that square root of AVE for malevolence (.779) and deceit (.793). Discriminant validity was not established among trust and distrust constructs. However, because they share second order formative constructs (i.e., the items formed a composite variable together), this was not problematic.

The result indicates a lack of discriminant validity between source credibility and integrity. This suggests that the items for source credibility and integrity are measuring a same construct. Thus, H1 was supported. Additionally, since integrity is a sub-construct (i.e., first order reflective construct) for trust, a second order formative construct, support for H1 suggests that source credibility measurements in this study are inclusive to the measurements for trust. Therefore, further investigations were focused on using trust in the place of source credibility.

Data Validation for PLS-SEM

Hypothesis testing for H2 through H7 was conducted using consistent PLS-SEM. Unlike CB-SEM, fit indices are mathematically less meaningful in PLS-SEM (Hair, Sarstedt, Ringle, & Mena, 2011). Instead, procedures to satisfy conservative standards for PLM-SEM is: (1) determine which constructs are formative or reflective; (2) establish factorial validity of formative and reflective constructs through convergent and discriminant validity; (3) validate if there is no issue with multicollinearity; (4) have strong reliabilities; and (5) establish that there is no common-method bias (Moody et al., 2014). For this reason, data validation for the indicators and constructs was conducted before the actual hypothesis testing.

Formative and reflective constructs. Formative constructs and reflective constructs are different in terms of the causal relationship between indicators (i.e., items, or measurements) and the construct. Specifically, if the construct is the reason for indicators the relationship is reflective; and if the indicators are the reason why the construct occurs, construct is formative (J. R. Edwards & Bagozzi, 2000). Additionally, formative construct is multidimensional and dependent upon other variables; while reflective construct is unidimensional (i.e., all the items are measureing the same aspect of a construct; Petter, Straub, & Rai, 2007). Correct assignments of formative or reflective constructs are important because the ramification of incorrect specification of formative or reflective constructs in PLS-SEM may lead to Type I or Type II error. Specifically, incorrectly specifying exogenous formative construct as reflective construct leads to upward bias in structural parameters, while misspecification of endogenous construct leads to downward bias (Petter et al., 2007).

Previous studies have identified whether the constructs used in this study are reflective or formative. Source credibility has been previously investigated (Sussman & Siegal, 2003) and verified to be a reflective construct (Petter et al., 2007). Message credibility measures used in this study is conceptualized as a reflective construct as well (Appelman & Sundar, 2016). Trust and distrust are well-established within PLS-SEM method (McKnight & Chervany, 2001; McKnight & Choudhury, 2006; McKnight et al., 2002; Moody et al., 2014) as a formative construct with sub-concepts and having it as a formative construct has been tested to be proper (Petter et al., 2007). Thus, as specification scheme for source credibility, message credibility, and trust are well-established and verified, and there was no theoretical or methodological rationale to contradict these findings, they were determined as formative or reflective constructs following earlier studies. Issue involvement, perception of bias, and perception of fake news were determined by following the rationales for specifying reflective and formative constructs reviewed by Petter et al. (2007). According to Petter et al. (2007) unidimensionality of the construct is one of them, which methodologically means that indicators are interchangeable and covary with each other. Thus, by following this rule, issue involvement (support one side or another to a certain degree on an issue), perception of bias, and perception of fake news (information is either true or fake intentionally) are specified as reflective constructs as they are unidimensional and simple constructs.

Two reflective constructs, political ideology and hostile media effect, each comprised of one measurement item. For SEM, The rule of thumb for number of items per a latent construct is three or more (e.g., Worthington & Whittaker, 2006). However, brevity of items required for a construct also depends on how complex the construct is, so a construct with one or two items can be used if the correlation between items within a construct is high, while they are fairly uncorrelated with other variables and the brevity of the concept is narrow (Yong & Pearce, 2013). And for PLS-SEM, constructs with one or two items can be used as the construct's measurement properties are less restrictive (Hair, Ringle, et al., 2011). Having single items for political ideology (people reporting to have liberal or conservative political stance) and hostile media effect (media being biased against a participant's belief) is justified by the constructs being conceptually narrow.

Establishing factorial validity of reflective constructs. First, individual items loadings on their respective constructs were examined. Although significant (i.e., $p < .05$) item loading above .70 is ideal (Kock, 2013), above .50 is thought to be acceptable in exploratory studies (Hair, Ringle, et al., 2011). Due to the exploratory nature of the current study, items were kept as long as the loadings were above .50. The total number of items in the model was 94. All of the items had significant ($p < .05$) loadings for their constructs. Among these, item "disposition to integrity" had the lowest loading of .665. Otherwise most of the remaining item loadings were above or barely under .70, meaning that the item loadings were above the threshold for an exploratory study. Thus, all the proposed item for the model was included in the model.

Next, convergent validity was examined through average variance extracted (AVE). As aforementioned, AVE is known to be a conservative indicator of convergent validity (Hair, Ringle, et al., 2011). All of the reflective constructs in the model showed convergent validity by having AVE that was larger than the threshold of .50.

Discriminant validity is achieved if Fornell-Larcker criterion (Fornell & Larcker, 1981), which requires a reflective construct to have square root of AVE that is larger than the correlations coefficients of the reflective construct and other reflective constructs Otherwise this means that the items for the reflective construct are measuring other constructs in the model as well (i.e., lack of discriminant validity; Zaiţ & Bertea, 2011). Although Heterotrait-Monotrait ratio (HTMT) is often thought as a more conservative and accurate measure of discriminant validity (e.g., Silva, Ringle, Silva, & Bido, 2014), as consistent PLS mimics covariance-based SEM, Fornell-Larcker criterion is more appropriate for assessing discriminant validity (Henseler, Ringle, & Sarstedt, 2015).

The result for discriminant validity is demonstrated in Table 37. Here, as was observed during the hypothesis testing of H1, some pairs of constructs lacked discriminant validity: source credibility and integrity, malevolence and deceit, benevolence and integrity, and disposition to malevolence and distrusting stance. Except for source credibility and integrity, other pairs formed a same formative construct (e.g., distrust was second-order formative construct of malevolence and deceit). Thus, trust and distrust measures that had discriminant validity were included without making any change, as in Moody et al. (2014). There was, however, no theoretical rationale to include source credibility and integrity (as part of trust) as distinct constructs in a single model despite lack of discriminant validity. Thus, source credibility and trust were alternately employed in the model.

Establishing factorial validity of formative constructs. Researchers have been traditionally established factorial validity of formative constructs through theoretical reasoning

(Diamantopoulos & Winklhofer, 2001). The formative constructs specified in this study were trust, distrust, disposition to trust, disposition to distrust, and hostile media effect. Indeed, trust and hostile media effect are theoretically distinct. Methodologically, following Moody et al. (2014), correlations between formative construct were examined. The correlation (Table 29) between formative variables show that strong correlation was observed only for two pairs of constructs: disposition to trust and trust, and disposition to distrust and distrust. However, theoretically this was predicted, therefore this was not problematic. For other pairs of correlations, only moderate or weak correlations were observed. Thus, factorial validity of formative constructs was established.

Validating multicollinearity issues. multicollinearity can affect the R^2 of the model by creating confounds among items. Multicollinearity is examined through variance inflation factor (VIF). Hair, Ringle, et al. (2011) suggested VIF of < 10 is good. Kock and Lynn (2012) suggested a more stringent < 5 as acceptable and < 3.3 as ideal. VIF scores for all items in the model are demonstrated in Table 36. All items were within acceptable range, and most items had ideal VIF scores. Items for message credibility and source credibility revealed to have acceptable but relatively higher VIF scores.

Reliability. Cronbach's Alpha and composite reliability (CR) were investigated to assess reliability of reflective constructs (Table 28). All reflective constructs employed in the model were above threshold for Cronbach's Alpha (>.70) and CR (>.80).

PLS Model Hypothesis Testing

Theoretical Model testing. Hypotheses were tested through models using PLS-SEM algorithm. Because results from H1 suggest that source credibility and integrity are not discriminant at measurement level (i.e., items for source credibility and integrity are interchangeable), they were alternately included in the model.

As demonstrated in Figure 1, the proposed theoretical predicted that: the political ideology will affect source credibility negatively (H2a) and distrust positively (H2b); political ideology is negatively related to hostile media effect (H3); higher source credibility predicts lower hostile media effect (H4a); higher distrust predicts lower hostile media effect (H4b); higher hostile media effect predicts lower media credibility (H5) and higher perception of fake news (H6); and higher media credibility predicts lower perception of fake news (H7). Statistical tests for the hypothesized model was carried out through consistent PLS algorithm (PLSc) and consistent PLS bootstrapping algorithm (cBootstrapping) from SmartPLS software (Dijkstra & Henseler, 2015).

The proposed theoretical model was tested. Here, distrust was employed in the place of source discredibility. Because results from H1 suggest that measurement items for source credibility and trust share some commonality, they were alternately included in the model, but not at the same time. When source credibility was used in the model (Figure 3), H3 ($t = 2.163$, $p = .031$), H4a ($t = 2.742$, $p = .006$), H5 ($t = 2.068$, $p = .039$), and H7 ($t = 19.109$, $p < .001$) were supported. Other hypotheses including those that are related to source credibility (H2a and H4a) failed to reject the null hypothesis. Result of this model testing is demonstrated in Table 30 and Table 31.

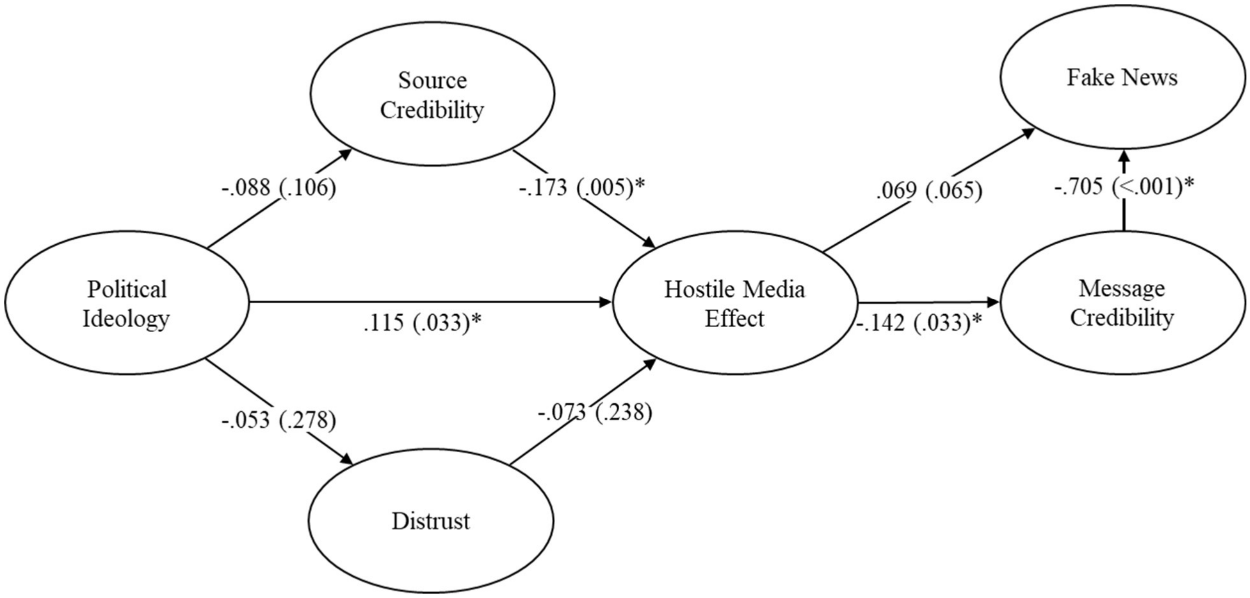

Figure 3. Hypothesis testing using Trust. Path coefficients (β) and *p*-values are shown.

Next, trust was used instead of source credibility in the model for hypothesis testing (Figure 4). Here, two additional second-order formative concepts, disposition to trust and disposition to distrust were introduced in the model. This decision was made because these dispositional constructs were developed together with trust and distrust to measure so the researchers can control for individual differences (Moody et al., 2014). Thus, the additional hypotheses were:

H9a. Disposition to trust positively predicts trust.

H9b. Disposition to distrust positively predicts distrust.

As expected, H9a ($t = 8.933$, $p < .001$) and H9b ($t = 16.628$, $p < .001$) were supported. Similar to the model with source credibility, H3 ($t = 2.019$, $p < .044$), H5 ($t = 2.184$, $p = .029$), and H7 ($t = 18.858$, $p < .001$) were again supported. Interestingly, contrary to the model with source credibility, H2a ($t = 2.292$, $p = .022$) was supported while H4a was only nearing the threshold ($t = 1.808$, $p = .071$). The result form this result is also described in Table 32 and Table 33.

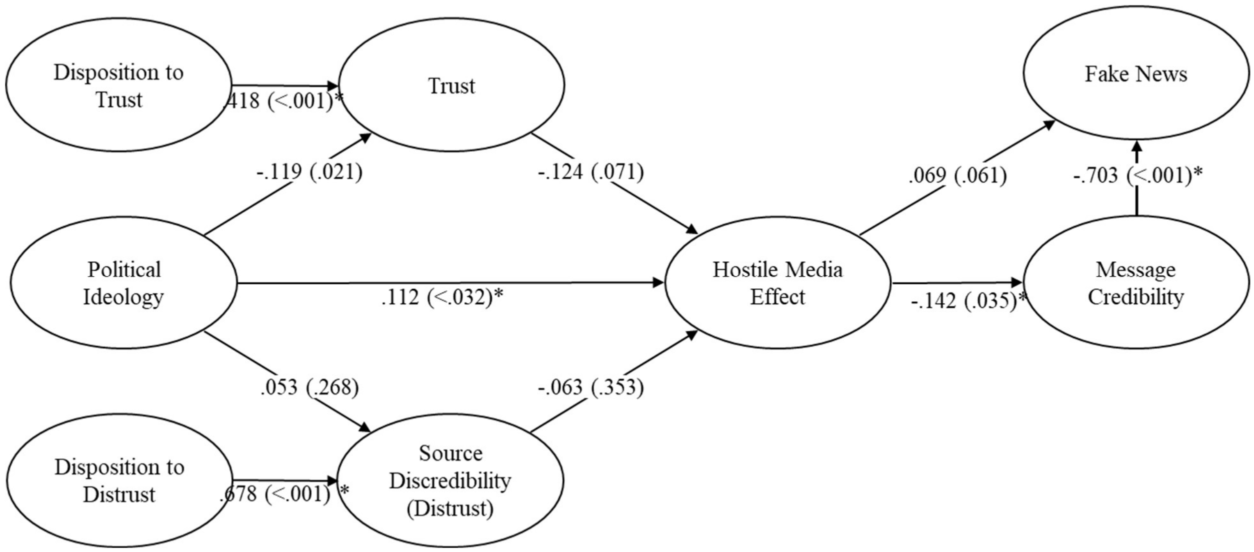

Figure 4. Hypothesis testing using Trust. Path coefficients (β) and *p*-values are shown.

The results from testing the theoretical model suggests that political ideology and hostile media effect are somewhat related to trust or source credibility, and hostile media effect is significantly related to message credibility; and hostile media effect may not be directly related to perception of fake news; and message credibility strongly explains fake news. Although preliminary testing revealed that hostile media effect is affected by the news topic condition in this study, meaningful relationship between hostile media effect and other constructs are observed. Thus, further analyses (e.g., multi-group analysis; MGA) that investigates the effect of group difference were not pursued. Instead, further analyses were conducted by incorporating additional construct, machine heuristic, in the model; and by testing direct relationship between trust or distrust and fake news.

Additional model testing. An alternate model was tested because (a) the effect of machine journalism was not included in the model, and (b) although hostile media effect and message credibility predicted perception of fake news, the relationship between trust or distrust and fake news were not tested. By partially replicating the conceptual approach by previous investigation on machine journalism (Waddell, 2018), an additional model was created.

The effect of machine journalism on other constructs (e.g., credibility and trust) was not incorporated in the originally proposed model. Because results for RQ1 unveiled the effect of machine journalism on credibility, trust, and distrust, they were hypothesized with direction and included in the model. Specifically, the additional model included the effect of machine journalism in the model by adding a construct, *machine heuristic.* Machine heuristic here is simply defined as the extent to which a person believes that the author of the article to be a machine. The machine journalism attribution precedes other constructs except for dispositional ones (e.g., disposition to trust, disposition to distrust, and political ideology), because this study purported the identity of the author, human versus machine, before exposure to the news article rather than asking the participants to infer the article to conclude if the author was a machine or human.

The result from RQ1 revealed statistically significant support for higher trust when the participants were told that the source was human, and partial support for higher distrust when the participants were told that the source was a machine. Thus, the following was hypothesized:

H10a: Machine heuristic is negatively related to trust.

H10b: Machine heuristic is positively related to distrust.

The theoretical design and the result of original model heavily relied on the relationship between message credibility and perception of fake news. However, literature review strongly suggested that perception of fake news is not only significantly related to message credibility, but also trust, distrust or source credibility (Tandoc et al., 2018; Tandoc et al., 2017). Meanwhile, the originally proposed model only tested the relationship between message credibility and fake news. Thus, predicting a relationship between trust and perception of fake news, and distrust and perception of fake news, is expected to result in explaining more variance for perception of fake news. Thus, it is hypothesized that:

H11a: Higher trust significantly predicts lower perception of fake news.

H11b: Higher distrust significantly predicts higher perception of fake news.

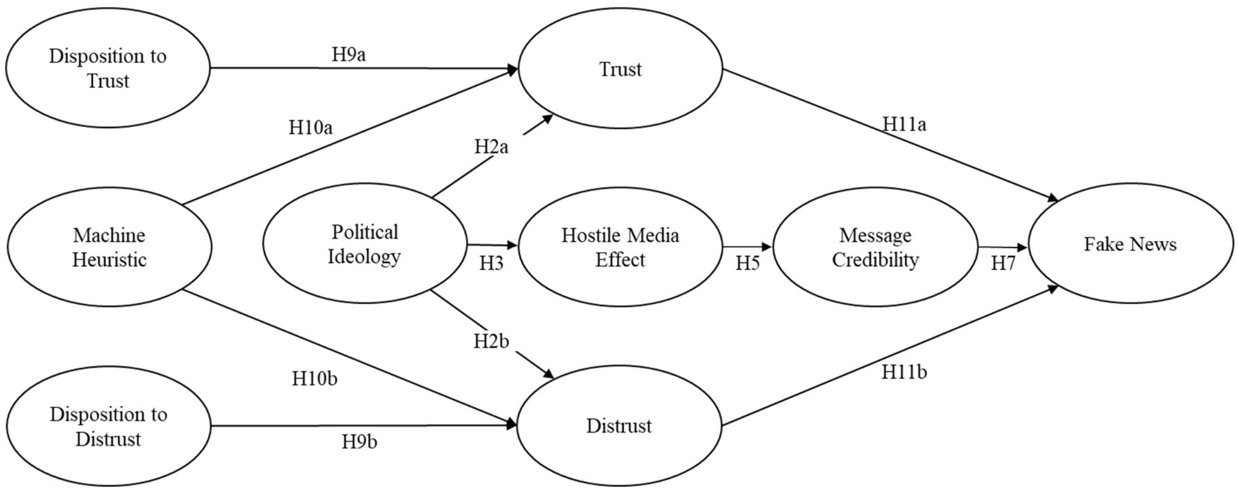

Figure 5. Additional Model.

To test the hypotheses in the additional model, a single-item construct named machine heuristic, which asked how much the participant thought that they were reading an article created by a machine, was added to the model. This source attribution construct was included instead of the manipulation check or the actual group assignment because the purpose of including this construct was to test the effect of thoughts about machine by replicating Waddell (2018). Additionally, PLS-SEM (and CB-SEM) does not calculate the model accurately when categorical variables – including dichotomous ones – are included in the model by default (Henseler & Fassott, 2010). There are algorithms (e.g., Wong, 2016) that are developed specifically to tackle this issue, however they are yet to be verified extensively. Thus, the continuous variable, machine journalism attribution, was employed instead of the actual group assignment.

The use of single item construct, machine heuristic, is justified by its narrowness of its concept. The rationale for this decision was similar to that of political ideology and hostile media effect as aforementioned. Machine heuristic asked where the participants perceived the author of the news article to be machine rather than human. Because the construct of machine heuristic is simple in this study, and the items were highly correlated with each other and not correlated with other variables, only the first item for machine heuristic was kept, making it a one-item-construct.

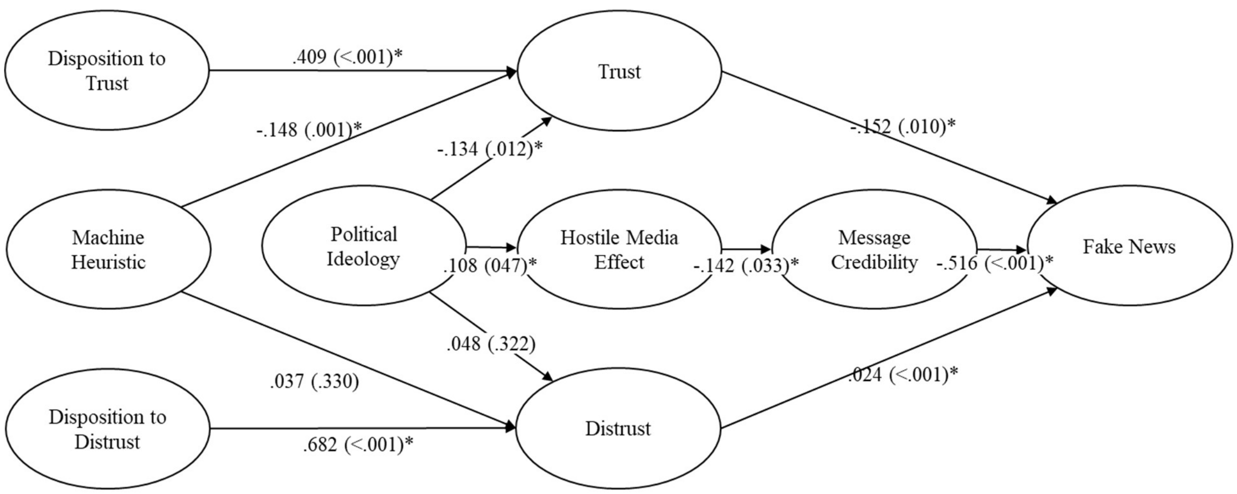

Figure 6. Addition Model testing. Path coefficients (β) and *p*-values are shown.

The result here revealed that, in addition to previously supported hypotheses, H10a (t =3.385, p = .001), H11a (t = 2.252, p < .010), and H11b (t = 8.691, p < .001) were supported. Notably, the variance of perception of fake news was better explained in the newer model (R^2 = .516) compared to the original model (R^2= 576). The result from this test is also described in Table 34 and Table 35.

Chapter 5: Discussion

This study investigated the effect of the perception of machine journalism on source credibility, media credibility, hostile media effect, and fake news. Additionally, this study examined the possibility of the existence of source discredibility.

Overview

RQ1 questioned if how people perceive a news article about a controversial topic differently if it was written by a machine journalist. Machine algorithm journalism perception led to less source credibility and trust. This result was in line with some of the previous findings (Waddell, 2018; Liu & Wei, 2018), but contradicted other earlier findings (Berger, 2014; Clerwall, 2014; Graefe et al., 2016). This may have been caused by different types of news article that were used in this study. This study contributes to the literature since it replicated earlier findings by using a more elaborately written article that may induce more intricate reaction from the readers, and it correspondingly employed a more broad array of measures. Also, as Waddell (2018) asserted, the contradicting result may be due to expectation violation. Considering that expectation violation predicts that because people expect machines to be free from biases, it is possible for people to find the machine to be less credible when the article produced by the machine is perceived to be biased. The expectation violation approach can possibly explain why earlier studies, which employed data driven articles with small potential for creating bias, found more credibility for machines (thus smaller possibility of expectation violation); while other studies, such as Liu & Wei (2018) and the current study, which had relatively more controversial topics, had lower credibility for machine journalism. In other words, finding bias in machine-written article might have led to stronger expectation violation. However, the current study was not able to find an effect of journalist condition on hostile media effect. This means that the expectation violation explanation regarding hostile media effect, which was originally proposed by Waddell (2018), was not supported. This result is not conclusive since expectation violation was not directly tested in the current study design. Thus, further investigation is required to find if expectation violation is a mediator for the relationship between hostile media effect and credibility.

RQ2 and H1 asked if credibility, trust, and distrust are distinct from discredibility in journalism. As predicted, distrust was identified as a discriminant construct rather than simply being a polar opposite of credibility on a single dimension. The theoretical prediction for this was methodologically supported as (a) discriminant validity for distrust was established compared to trust and source credibility; (b) and distrust manifested differentiating effects compared to source credibility and trust on other constructs as journalist belief only affected trust but not distrust, while distrust better predicted perception of fake news. This discovery suggests that there might be an opportunity for a myriad of application in research by viewing discredibility as a distinct concept from credibility.

The relationship between trust and credibility was assessed in the context provided in this study. As mentioned in the literature review, trust and credibility has long been thought to be closely related to each other. However, there is a gap in literature which empirically tested the relationship in journalism context. The current study empirically investigated their relationship and found that indeed they are closely related. Specifically, the statistical result suggests that the source credibility measurements that were employed in this study measures the same construct as integrity measurements, which is a sub-concept of trust.

This finding does not necessarily mean that credibility should be treated as a sub-concept of trust. Theoretically, source credibility in journalism is conceptualized to have two sub-concepts which are trustworthiness and expertise – which closely matches the sub-concepts of trust, benevolence, competence, and integrity. Both have sub-concepts that are rooted upon the perception of the ethical intention and professional ability of the source. Categorizing trust into cognitive and affective parts (Johnson & Grayson, 2005) also resembles the subconstructs of trust, trustworthiness and expertise. The result suggests that the source credibility measurement that was used in this study may not be sensitive enough to show divergent validity between its sub-concepts and limited to assessing the trustworthiness, but not expertise, of source credibility. Therefore, the result implies that future studies on credibility should incorporate source credibility measures that can differentiate its sub-concepts sensitively, possibly by incorporating trust measures that are found to be useful in this study.

Finding lack of discriminant validity between source credibility items and integrity items (as first-order reflective construct for trust) is not sufficient to conclude the conceptual relationship between source credibility and trust. Rather, the findings in this study is limited to the relationships between specific measures of trust (McKnight & Choudhury, 2006) and source credibility (Bhattacherjee & Sanford, 2006). Further investigation, possibly by employing different items is required to better understand the relationship between the two concepts.

RQ3 and H2 to H11 questioned the relationship between hostile media effect and credibility/discredibility of the source and the message especially in case of machine-generated news. Hostile media effect was replicated, similar to the results from Schmitt et al. (2004).

The relationship between hostile media effect and other constructs were weaker than expected. Hostile media effect was significantly related to source credibility, message credibility, and political ideology, but not trust. This is suspected to be due to the unintended effect of news topic on hostile media effect. Specifically, variance between news articles may have led to lack of relationship between hostile media effect and credibility. This unexpected effect of news topic on hostile media effect is interesting, considering that hostile media effect researches often employ a single stimulus. Therefore, this result suggests that future study specifically focusing on the characteristics of the news report (e.g., framing, information processing, or topic) might be able to reveal novel findings regarding hostile media effect.

Perception of fake news has also been examined. The relationship between credibility between fake news and credibility was obviously predicted in the literature (Tandoc et al., 2017). The result from PLS-SEM model suggest that the credibility of the message as well as trust and distrust have large impacts on perception of fake news, as more variance of perception of fake news was explained in the additional model compared to the original model. Comparing the significance of difference in explanatory power for the two models should is better done with CB-SEM, where model fits can be tested for significant difference. This may require a larger sample size, however. Also, as much as fake news depends on the credibility and trust perception towards the mediated experience, distrust also differently plays a role in bolstering the perception of fake news. This implies that the effort towards overcoming the issue of fake news should be focused more towards finding a way to improve message credibility along with source credibility, and also focus on understanding the effect of distrust (and possibly discredibility) on perception of fake news.

Limitations and Future Research

This study employed source credibility and message credibility as distinct constructs and found their differentiating effects on perception of machine journalism and fake news. While the relationship between source credibility and the information processing of the message can be investigated thoroughly (e.g., Petty, Cacioppo, & Schumann, 1983; Priester et al., 2009; Priester

& Petty, 1995, 2003), this study was only able to report that the two are correlated. Future research should integrate information processing theories such as ELM or HSM to further explain how source discredibility differently affect message credibility in detail.

A more thorough manipulation check for machine-journalist condition was missing. Specifically, Nass and Moon (2000) and Sundar and Nass (2000) explored the different possible mechanisms of how or why CASA occurs. Accordingly, this study assumed that people will react to algorithm condition mindlessly, thus treating the algorithm as if it were a social actor. In other words, this study assumed that people will operate as CASA paradigm predicts by viewing the algorithm as independent social actors. However, there is a possibility that participants may have anthropomorphized the machine. Or, more critical to the research questions of this study, participants' perception of credibility may have been directed toward the programmer behind the algorithm, which would mean the source credibility in machine journalist condition are actually measuring source credibility of a human programmer. In line with this issue, Liu and Wei (2018) found that the effect of machine journalism varied depending on news organizations. Specifically, machine journalism led to higher credibility only when the news organization condition was New York Times, while having Fox as a news organization for the machine journalism did not lead to any difference in credibility. This might also have been the case, such that people might have thought of the gatekeeper for the machine algorithm and made credibility judgement for the human behind the machine. These alternate scenarios, albeit rejected in earlier CASA studies, could have been easily tested rather than kept as an assumption in this study.

In relation to CASA, machine heuristic is thought to be a multidimensional construct (e.g., Sundar & Kim, 2019). The construct machine heuristic in the current study however, was improvised by using a single-item construct. This limits the implication for the findings regarding machine heuristic since the extent to which the intelligence of the machine algorithm was perceived by participants was not tested in this study. In other words, participants' idea of machine journalist may have ranged from a low-level algorithm to a high-level artificial intelligence – and this was not tested. Thus, findings from the additional model is limited. More valid and reliable measures for machine heuristic should be employed in the future to ensure more meaningful results.

Trust and distrust measure used in this study incorporates trait measures of trust and distrust, which are named disposition to trust and disposition to distrust. As most communication or journalism research on source credibility relies predominantly on the state measure only, introducing a trait measure may lead us to further understand the concept of credibility. However, in this study disposition variables (i.e., trait variables) mostly only predicted their respective state variables and no other meaningful relationships were discovered. Furthermore, the current study did not include other important trust measures from the original questionnaire (Moody et al., 2014; originally from McKnight et al., 2002). For instance, the trust intention measure from (Moody et al., 2014) are trust-specific intention measures, rather than generic intention measures. In other words, the trusting intention items measures behavioral intentions that are rooted from trust specifically. Considering that the majority of the source credibility literature is related to persuasion, applying trust (or credibility) intention measures, which corresponds well with state and trait measures, seem to be promising for future research.

One issue with the trust/distrust measure (Moody et al., 2014) that was introduced to journalism context in this study is its volume. If one intends to take advantage of the full suite of trust and distrust measures, the number of questions amount to 78. This study, even though attempted to use only part of the whole questionnaire, had limitations in terms of study design, since the cognitive fatigue of participants due to the large number of measurement items was of concern. Thus, development of a shorter version of this questionnaire would be helpful in the future. Additionally, although this study investigated the convergent and discriminant validity between trust and distrust, development of measurement items for discredibility was not pursued.

Hostile media effect was replicated, but this study failed to find more interesting relationship with other constructs. The relationship between hostile media effect and machine heuristic for instance, was not significant. This may be due to the issue with measuring hostile media effect with different news topics. A multi-group analysis would be able to explore the differentiating effect of hostile media depending on news topics. Including other mediators in the model may also help find a more meaningful result. Possible explanations or mediators include urgency, third person effect, and argument quality of the article. In sum, although the stimuli presentation was designed to accomplish ecological validity to some extent, future research should find a more reliable design to prevent confounds. One possible solution to this issue is to run a within- or mixed-design experiment, where participants are exposed to different stimuli.

As in many other communication studies, the findings in this study is fundamentally limited to the stimuli and the context that was provided to the participants in this study. To extend findings from this study, the differentiating effects of machine versus human journalist found in this study should be studied using different types of articles. The discriminant validity that was validated between credibility and discredibility, and the convergent validity that was found between source credibility and trust, are also limited to the stimuli and the condition employed in this study. Further exploration on different topics, media, or context is required to generalize the findings from this study.

Finally, due to the sample bias originating from recruitment method, some characteristics of the sample was slanted compared to general population. Specifically, the sample in this study showed a liberal slant in terms of political ideology. Also, since people who participate in online recruitment platforms are expected to be more tech-savvy, the participants in this study may have different idea about machines compared to general population.

Conclusion

Source credibility is conceptually and methodologically well-established in journalism. This study attempted to add another block to the knowledge by proposing to treat source discredibility as a distinct concept from source credibility. In an attempt to do so, this study tried to manipulate the author of the news article and relate source credibility and discredibility to other concepts using factorial and modelling approach. The result indicated meaningful difference to support the idea that source credibility and source discredibility may be distinct concepts. Specifically, the reflective sub-constructs of trust and distrust showed discriminant validity, meaning that items for the two constructs were measuring distinct psychological concepts, rather than detecting the two polar opposites of a singular concept.

In addition to trust and distrust measuring distinct concepts within journalism context, the two constructs had differentiating relationships with other constructs. Machine heuristic and political ideology were negatively related to trust, replicating earlier findings. This study, however, was not able to find distinct relationship between distrust and other constructs compared to trust. Follow up studies will be conducted to identify how these seemingly singular concepts may exhibit different outcomes.

Hostile media effect was observed in this study, and its relationship between message credibility was observed. Relationships with other constructs were limited, which is possibly due to the confound caused by having three different news topics. This finding suggests that comparing the effect of topic on hostile media effect, which was not the primary focus of hostile media effect literature, may reveal novel findings in hostile media bias research.

This study contributes to CASA paradigm as the finding shows that machine is not always perceived to be more trustworthy or credible compared to humans. This result was contrary to our general belief of machines (e.g., Sundar & Kim, 2019). Because similar findings were reported in earlier machine journalism as well, the result should not be considered as anomaly. Thus, further investigation must be followed to pinpoint the underlying mechanisms for this result.

Machine-algorithm journalist context was used in this study as a starting point for the line of study area which I plan to explore – if we accept the assumption of CASA, how exactly people will treat algorithms or artificial intelligence as a "different type of humans." This study found some clue for future exploration, in that participants in this study trusted or distrusted algorithm as if they were people but had different appraisal in terms of credibility and trust for machine versus human. Further implications for this difference should be pursued by theoretically and empirically identifying the mediators and moderators for this difference.

Appendix A: Measures

Age

What is your date of birth?

Month	▼ January ...
Day	▼ 1 ...
Year	▼ 2019 ...

Education

What is the highest level of school you have completed or the highest degree you have received?

o Less than high school degree

o High school graduate (high school diploma or equivalent including GED)

o Some college but no degree

o Associate degree in college (2-year)

o Bachelor's degree in college (4-year)

o Master's degree

o Doctoral degree

o Professional degree (JD, MD)

Ethnicity

Choose one or more races that you consider yourself to be:

▢ White/Caucasian

▢ Black or African American

▢ Hispanic

▢ Asian

▢ American Indian or Alaska Native

▢ Native Hawaiian or Pacific Islander

▢ Other ____

Are you Spanish, Hispanic, or Latino or none of these?

o Yes

o None of these

Sex/Gender

What is your sex?

o Male

o Female

o Other

o Prefer not to share

Income

Information about income is very important to understand. Would you please give your best guess?Please indicate the answer that includes your entire household income in (previous year) before taxes.

o Less than $10,000

o $10,000 to $19,999

o $20,000 to $29,999

o $30,000 to $39,999

- $40,000 to $49,999
- $50,000 to $59,999
- $60,000 to $69,999
- $70,000 to $79,999
- $80,000 to $89,999
- $90,000 to $99,999
- $100,000 to $149,999
- $150,000 or more

Political affiliation

Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent, or something else?

- Republican
- Democrat
- Independent
- Other ____
- Prefer not to disclose

Political ideology *(7-point Likert-type scale; 1:Extremely liberal – 7:Extremely conservative)*

Here is a 7-point scale on which the political views that people might hold are arranged from extremely liberal (left) to extremely conservative (right). Where would you place yourself on this scale?

Issue involvement *(7-point Likert-type scale; 1:Strongly disagree – 7:Strongly agree)*

Please choose the answer that best depicts your general idea on these statements:

I am a strong supporter of gun control.

I am a strong supporter of gun rights. (R)

I am a strong supporter of pro-environmental policies.

I am a strong supporter of policies that creates more jobs. (R)

I am a strong supporter of stricter regulation of immigration through US-Mexico border. (R)

I am a strong supporter of a more lenient regulation of immigration through US-Mexico border.

Issue involvement II

If I had to choose between the two policies, I would support:

o Gun Rights

o

o

o Neutral

o

o

o Gun Control

If I had to choose between the two policies, I would support: (R)

o Economy

o

o

- o Neutral
- o
- o
- o Environment

Disposition to trust and disposition to distrust *(7-point Likert-type scale; 1:Strongly disagree – 7:Strongly agree)*

Please choose the answer that best depicts your general ideas about trusting others:

Disposition to benevolence:

In general, people really do care about the well-being of others.

The typical person is sincerely concerned about the problems of others.

Most of the time, people care enough to try to be helpful, rather than just looking out for themselves.

Disposition to competence:

I believe that most professional people do a very good job at their work.

Most professionals are very knowledgeable in their chosen field.

A large majority of professional people are competent in their area of expertise.

Disposition to integrity:

In general, most folks keep their promises.

I think people generally try to back up their words with their actions.

Most people are honest in their dealings with others.

Trusting Stance:

I usually trust people until they give me a reason not to trust them.

I generally give people the benefit of the doubt when I first meet them.

My typical approach is to trust new acquaintances until they prove I should not trust them.

Disposition to malevolence:

I worry that journalists are usually concerned about their own good.

It concerns me a lot that journalists pretend to care more about their readers than they really do.

I fear that most journalists inwardly dislike putting themselves out to help out their readers.

Disposition to incompetence:

I am troubled that many journalists are not as knowledgeable in their product/service area as you would expect.

I am cautious because I believe that most journalists do a haphazard job at what they do.

Concern is justified, since many journalists are not really competent in their area of expertise.

Disposition to deceit:

Unfortunately, most journalists would tell a lie if they could gain by it.

It's a troubling fact that journalists don't always hold to the standard of honesty they claim.

Sadly, most journalists would cheat their customers if they thought they could get away with it.

Distrusting stance:

I'm usually cautious about relying on people when I first work with them.

When I first meet people, I tend to watch their actions closely.

I typically have suspicious feelings towards new acquaintances until they prove to me that I can trust them.

I am hesitant to trust people until they have shown themselves to be reliable.

Trust and Distrust *(7-point Likert-type scale; 1:Strongly disagree – 7:Strongly agree)*

Please choose the answer that best depicts your ideas about the journalist:

Benevolence:

I believe that the journalist would act in my best interest.

If I required help, the journalist would do their best to help me.

The journalist is interested in my well-being, rather than their own.

Competence:

The journalist is competent and effective in providing the news.

The journalist performed their role of providing information for the news very well.

Overall, the journalist is capable and proficient provider of news.

In general, the journalist is very knowledgeable about the news topic.

Integrity:

The journalist is truthful in their reporting.

I would characterize the journalist as honest.

The journalist would keep their commitments.

The journalist would be sincere and genuine.

Malevolence:

I worry that the journalist is only concerned about their own interests.

It concerns me a lot that the journalist pretends to care more about me than the journalist really does.

I fear that the journalist inwardly dislikes putting itself out to help other buyers.

Incompetence:

I am troubled that the journalist is not as knowledgeable in their field as I would expect.

I am cautious because I believe that the journalist does a haphazard job at what they do.

Concern is justified, since the journalist is not really competent in their area of expertise.

Deceit:

Unfortunately, the journalist would tell a lie if they could gain by it.

It's a troubling fact that the journalist won't always hold to the standard of honesty they claim.

Sadly, most journalists would cheat their customers if they thought they could get away with it.

Perceived Bias (hostile media effect) – Gun policy*: (11-point Likert-type scale; 1:Strongly biased against – 11:Strongly biased in favor of)*

Please choose the answer that best depicts your ideas about the news article:

Would you say that this article was biased in favor of the supporters of gun control?

Would you say that this article was biased in favor of the supporters of gun rights? (R)

Perceived Bias (hostile media effect) – Environment policy: *(11-point Likert-type scale; 1:Strongly biased against – 11:Strongly biased in favor of)*

Would you say that this article was biased in favor of the supporters of more jobs over protecting environment?

Would you say that this article was biased in favor of the supporters of protecting environment over more jobs? (R)

Perceived Bias (hostile media effect) – Immigration: *(11-point Likert-type scale; 1:Strongly biased against – 11:Strongly biased in favor of)*

Would you say that this article was biased in favor of the supporters of changing the immigration policy? (R)

Would you say that this article was biased in favor of the supporters of keeping the immigration policy?

Source credibility: *(7-point Likert-type scale; 1:Strongly disagree – 7:Strongly agree)*

Please choose the answer that best depicts your ideas about the journalist:

The journalist providing the news was knowledgeable on this topic.

The journalist providing the news was trustworthy.

The journalist providing the news was credible.

The journalist providing the news appeared to be an expert on this topic.

Message credibility: *(7-point Likert-type scale; 1:Describes very poorly– 7:Describes very well)*

How well do the following adjectives describe the content you just read?

accurate

authentic

believable

Argument quality & attention checks: *(7-point Likert-type scale; 1:Strongly disagree – 7:Strongly agree)*

Please choose the answer that best describes your idea about the news article.

The information provided in the news article was informative.

The information provided in the news article was helpful.

The information provided in the news article was valuable.

The information provided in the news article was persuasive.

The article that I read was written by a machine algorithm journalist.

The article that I read was written by a human journalist.

Perceived fake news: *(7-point Likert-type scale; 1:Strongly disagree – 7:Strongly agree)*

Please choose the answer that best describes your idea about the authenticity of the news article.

I believe the news article relies on facts

I believe the writer intends to mislead

The news article is fake news

This news article is true

Manipulation checks:

The article that I read was written by:

o A machine algorithm

o A human journalist

The news article that I read was about:

o Gun ownership legislation

o Immigration policy change

o Jobs and environment

Appendix B: Stimuli

Stimuli 1: Gun Control vs. Gun Rights

New bill for gun ownership to hold vote

The House on Wednesday will hold vote on gun control legislation in years, bringing to the floor two bills regarding the background check system for gun purchases.

But while the Democratic-led House is expected to pass the bills, they're unlikely to be considered in the GOP-controlled Senate.

Here's what you need to know about the legislation.

One bill, H.R. 8, would require background checks for private transactions, such as purchases online and at gun shows. Currently, only federally licensed firearms dealers, importers and manufacturers are required to conduct background checks on customers under federal law.

The other bill, H.R. 1112, would extend to at least 10 days the amount of time firearms dealers must wait for a response from the background check system before the sale can proceed. Currently, they can make the sale if they haven't received a response in three days.

Advocates say the bills would close loopholes in the background check system. For example, the gunman who killed nine people at the Emanuel African Methodist Episcopal Church in Charleston, S.C., in 2015, had a record that, under the law, would have made him ineligible to buy a gun, according to PolitiFact.

Opponents say background checks are worthless unless they are paired with a national gun registry. They argue the changes would not have prevented the recent mass shootings while the cost and extra hurdle to get a background check could be a significant obstacle for those trying to defend themselves.

A Shooting survivor and former Rep. Gabby Giffords, who co–founded a gun–control group after leaving Congress, is lobbying for the legislation on Capitol Hill this week.

But Louisiana Rep. Steve Scalise, another shooting survivor, opposes the legislation. Scalise said the bill would not have stopped his gunman and only take away the rights of gun owners.

The bills passed out of the House Judiciary Committee this month on party-line votes. The House votes are expected to be similar, with just a handful of Republicans likely to vote for the legislation and a handful of Democrats expected to oppose the bills.

Stimuli 2: Jobs vs. Environment

Do environmental regulations kill jobs?

Finding a middle ground is difficult, especially in the midst of heated political wrangling over how to cope with the sputtering economy. Businesses are focusing almost entirely on the costs. Environmental groups, meanwhile, tally up the benefits without paying much heed to the costs.

Republicans and business groups say yes, arguing that environmental protection is simply too expensive for a battered economy. Many economists agree that regulation comes with undeniable costs that can affect workers. Factories may close because of the high cost of cleanup, or owners may relocate to countries with weaker regulations.

But many experts say that the effects should be assessed through a nuanced tally of costs and benefits that takes into account both economic and societal factors. Some argue that the costs can be offset as companies develop cheaper ways to clean up pollutants, and others say that regulation is often blamed for job losses that occur for different reasons, like a stagnant economy.

The question of just how much environmental regulation hurts jobs is a particularly delicate one as leaders in Washington debate the best ways to address the nation's stubbornly high unemployment rate.

Michael Greenstone, an economist at the Massachusetts Institute of Technology, conducted studies that measure job losses related to environmental rules. In researching the amendments to the Clean Air Act that affected polluting plants from 1972 and 1987, he found that those companies lost almost 600,000 jobs compared with what would have happened without the regulations.

But Mr. Greenstone has also conducted research showing that clean air regulations have reduced infant mortality and increased housing prices. Many economists argue the costs of regulations are dwarfed by the gains in lengthened lives, reduced hospitalizations and other health benefits, and by economic gains like the improvement to the real estate market.

Business groups also tend to cite regulation even if other factors are involved, critics say. The cement industry is currently warning that as many as 18 of the 100 cement plants currently operating in the United States could close down because of proposed stricter standards for sulfur dioxide and nitrogen oxide emissions, resulting in the direct loss of 13,000 jobs.

Some cement plants could be at risk simply because of the economy. With the housing market on its knees, demand for cement is down by about 40 percent from its prerecession peak. According to Andy O'Hare, vice president for regulatory affairs at the Portland Cement Association, a trade group, about a third of the cement plants in the country are being shut off every other month.

"My view is that the Republican claim that 'job-killing regulation' is a redundancy is as ridiculous as the left-wing view that 'job-killing regulation' is an oxymoron," said Cass Sunstein, head of the White House Office of Information and Regulatory Affairs. "Both are silly political claims that have no place in a serious discussion."

Stimuli 3: Immigration

Advisory group recommends changes to migrant processing

A federal advisory group is calling for significant changes to how the federal government deals with the surge of migrant families that officials say is overwhelming the southern border.

In a draft report unveiled Tuesday, a committee of the Homeland Security Advisory Council called on the Trump administration to immediately establish three to four regional migrant processing centers along the southwest border with Mexico. The bipartisan group also endorsed changes to an agreement that generally bars the government from keeping children in immigration detention for more than 20 days.

The report comes as border officials are struggling to cope with an influx of Central American families, with U.S. Border Patrol apprehending a record-setting 53,000 families in March.

"There is a real crisis at our border," say the authors, who include immigration experts, lawyers, former federal officials and a medical doctor. "An unprecedented surge in family unit migration from Central America is overwhelming our border agencies and our immigration system. This crisis is endangering children."

The report calls for the establishment of new centers where migrant families would be processed by immigration officials, receive medical care and have their asylum cases heard by immigration judges. And they want to see a similar processing center established in Guatemala, near that country's border with Mexico, so migrants can make asylum claims without having to make the dangerous trek to the U.S.

Acting Homeland Security Secretary Kevin McAleenan welcomed the report, releasing a statement Tuesday night saying, "The reasonable changes proposed by this nonpartisan panel could dramatically reduce migration of family units from Central America, help eliminate dangerous and illegal border crossings, as well as improve the care of children who are brought on this harrowing journey."

The Trump administration supports asylum changes and other steps to slow the influx of migrants at the border as President Donald Trump tries to make good on his 2016 campaign promises and energize his base going into 2020.

But Katharina Obser of the Women's Refugee Commission said many of the ideas in the report would only exacerbate the problem.

"It is long overdue for the government to invest its existing funds in a comprehensive, legal and humane approach to protection at our borders," she said, but many of the report's recommendations "would do little to better care for vulnerable families and children seeking protection in the United States."

If implemented, the recommendations could "exacerbate the situation at the border, further traumatize and endanger families and children and betray our legal and moral obligations to ensure access to a safe and fair asylum process," she said.

Appendix C: Tables

Table 1

Gender, Ethnicity, and Political Party Affiliation

Gender	*N*	%
Male	175	43.75
Female	220	55
Other	3	.75
Not disclosed	2	.5
Ethnicity		
White/Caucasian	339	84.75
Black/African American	30	7.5
Hispanic	27	6.75
Asian	27	6.75
Native American/Alaska Native	6	1.5
Other	0	0
Political Party Affiliation		
Republican	65	16.25
Democrat	205	51.25
Independent	113	28.25
Other	12	3
Not disclosed	5	1.25

Table 2

Number of participants per conditions

News Topic	Journalist	*N*
Gun Policy	Machine	65
	Human	66
	Total	131
Immigration Policy	Machine	62
	Human	69
	Total	131
Environment Policy	Machine	70
	Human	68
	Total	138

Table 3

Skewness, kurtosis, and Shapiro-Wilk test results for dependent variables

Variables	*Skewness*	*Kurtosis*	*Statistic*	*df*	*p*
Political Ideology	.561	-.527	.936	400	.000
Disposition to Trust	-.356	.212	.990	400	.009
Disposition to Distrust	-.166	-.461	.992	400	.026
Trust	-.484	.768	.984	400	.000
Distrust	.277	-.291	.988	400	.002
Source Credibility	-.560	.440	.973	399	.000
Message Credibility	-.812	.444	.938	400	.000
HME Index	.178	.751	.988	400	.003
Issue Involvement Index	.389	-.986	.922	400	.000

Table 4

Fixed-Effects ANOVA results using Source Credibility as the criterion

Predictor	Sum of Squares	*df*	Mean Square	*F*	*p*	partial η^2	partial η^2 90% CI [LL, UL]
(Intercept)	1455.90	1	1455.90	1028.33	.000		
Journalist	0.90	1	0.90	0.63	.427	.00	[.00, .01]
News Topic	0.19	2	0.10	0.07	.935	.00	[.00, .00]
Journalist x News Topic	0.23	2	0.12	0.08	.923	.00	[.00, .00]
Error	556.41	393	1.42				

Note. LL and UL represent the lower-limit and upper-limit of the partial η^2 confidence interval, respectively.

Table 5

Means and standard deviations for Source Credibility as a function of a 2(Journalist) X 3(News Topic) design

	News Topic							
	Gun		Immigration		Environment		Marginal	
Journalist	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Machine	4.77	1.02	4.69	1.22	4.75	1.15	4.74	1.13
Human	4.94	1.23	4.76	1.30	4.91	1.20	4.87	1.24
Marginal	4.85	1.13	4.73	1.26	4.83	1.17		

Note. M and *SD* represent mean and standard deviation, respectively.

Table 6

Fixed-Effects ANOVA results using Message Credibility as the criterion

Predictor	Sum of Squares	*df*	Mean Square	*F*	*p*	partial η^2	partial η^2 90% CI [LL, UL]
(Intercept)	3101.55	1	3101.55	1063.70	.000		
Journalist	1.56	1	1.56	0.54	.464	.00	[.00, .01]
News Topic	12.67	2	6.33	2.17	.115	.01	[.00, .03]
Journalist x News Topic	1.04	2	0.52	0.18	.837	.00	[.00, .01]
Error	1148.83	394	2.92				

Note. LL and UL represent the lower-limit and upper-limit of the partial η^2 confidence interval, respectively.

Table 7

Means and standard deviations for Message Credibility as a function of a 2(Journalist) X 3(News Topic) design

	News Topic							
	Gun		Immigration		Environment		Marginal	
Journalist	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Machine	6.91	1.53	6.46	1.73	6.31	1.95	6.56	1.76
Human	7.13	1.47	6.90	1.75	6.75	1.75	6.92	1.66
Marginal	7.02	1.50	6.69	1.75	6.53	1.86		

Note. M and *SD* represent mean and standard deviation, respectively.

Table 8

Two-way ANCOVA results using Disposition to Trust as covariate and Trust as the criterion

Source	Sum of Squares	*df*	*F*	*p*
D. trust	56.254	1	73.374	<.001
Journalist	7.890	1	10.290	<.001
News Topic	1.002	2	0.654	.520
Journalist x News topic	.876	2	.571	.565
Error	301.302	393		

Table 9

Means and standard errors for Trust as a function of a 2(Journalist) x 3(News Topic) design with Disposition to Trust as a covariate

Journalist	News Topic	*M*	*Standard Error*	*Lower Limit*	*Upper Limit*
Machine	Gun	4.57	.109	4.35	4.78
Human	Gun	4.86	.108	4.65	5.07
Machine	Immigration	4.52	.112	4.30	4.74
Human	Immigration	4.68	.105	4.47	4.88
Machine	Environment	4.43	.105	4.23	4.64
Human	Environment	4.82	.107	4.61	5.03

Table 10

Two-way ANCOVA results using Disposition to Distrust as covariate and Distrust as the criterion

Source	Sum of Squares	*df*	*F*	*p*
D. distrust	196.560	1	263.062	<.001
Journalist	.382	1	.511	.475
News Topic	.483	2	.323	.724
Journalist x News topic	1.389	2	.930	.396
Error	293.650	393		

Table 11

Means and standard errors for Distrust as a function of a 2(Journalist) x 3(News Topic) design with Disposition to Distrust as a covariate

Journalist	News Topic	*M*	*Standard Error*	*Lower Limit*	*Upper Limit*
Machine	Gun	3.29	.107	3.08	3.50
Human	Gun	3.22	.106	3.01	3.43
Machine	Immigration	3.17	.110	2.96	3.39
Human	Immigration	3.39	.104	3.19	3.59
Machine	Environment	3.18	.103	2.98	3.38
Human	Environment	3.22	.105	3.02	3.43

Table 12

Fixed-Effects ANOVA results using Issue Involvement as the criterion

Predictor	Sum of Squares	*df*	Mean Square	*F*	*p*	partial η^2	partial η^2 90% CI [LL, UL]
(Intercept)	234.02	1	234.02	421.98	.000		
Journalist	0.00	1	0.00	0.00	.979	.00	[.00, 1.00]
News Topic	28.33	2	14.16	25.54	.000	.11	[.07, .16]
Journalist x News Topic	0.10	2	0.05	0.09	.917	.00	[.00, .00]
Error	218.50	394	0.55				

Note. LL and UL represent the lower-limit and upper-limit of the partial η^2 confidence interval, respectively.

Table 13

Means and standard deviations for Issue Involvement as a function of a 2(Journalist) X 3(News Topic) design

	News Topic							
	Gun		Immigration		Environment		Marginal	
Journalist	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Machine	1.90	0.82	0.98	0.49	1.63	0.90	1.51	0.85
Human	1.89	0.89	0.90	0.47	1.59	0.75	1.45	0.83
Marginal	1.90	0.86	0.94	0.48	1.61	0.83		

Note. M and *SD* represent mean and standard deviation, respectively.

Table 14

Fixed-Effects ANOVA results using HME Index as the criterion

Predictor	Sum of Squares	*df*	Mean Square	*F*	*p*	partial η^2	partial η^2 90% CI [LL, UL]
(Intercept)	236.30	1	236.30	168.98	.000		
Journalist	0.38	1	0.38	0.27	.601	.00	[.00, .01]
News Topic	61.56	2	30.78	22.01	.000	.10	[.06, .15]
Journalist x News Topic	2.31	2	1.16	0.82	.439	.00	[.00, .02]
Error	550.98	394	1.40				

Note. LL and UL represent the lower-limit and upper-limit of the partial η^2 confidence interval, respectively.

Table 15

Means and standard deviations for HME Index as a function of a 2(Journalist) X 3(News Topic) design

	News Topic							
	Gun		Immigration		Environment		Marginal	
Journalist	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Machine	1.91	1.17	0.69	1.17	1.88	1.34	1.51	1.35
Human	1.80	1.03	0.96	1.08	1.94	1.28	1.56	1.21
Marginal	1.85	1.10	0.83	1.12	1.91	1.30		

Note. M and *SD* represent mean and standard deviation, respectively.

Table 16

Fixed-Effects ANOVA results using Political Ideology as the criterion

Predictor	Sum of Squares	*df*	Mean Square	*F*	*p*	partial η^2	partial η^2 90% CI [LL, UL]
(Intercept)	744.62	1	744.62	105.60	.000		
Journalist	0.24	1	0.24	0.03	.855	.00	[.00, .01]
News Topic	17.33	2	8.66	1.23	.294	.01	[.00, .02]
Journalist x News Topic	30.05	2	15.03	2.13	.120	.01	[.00, .03]
Error	2778.08	394	7.05				

Note. LL and UL represent the lower-limit and upper-limit of the partial η^2 confidence interval, respectively.

Table 17

Means and standard deviations for Political Ideology as a function of a 2(Journalist) X 3(News Topic) design

	News Topic							
	Gun		Immigration		Environment		Marginal	
Journalist	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Machine	3.38	2.30	2.89	2.67	3.60	2.69	3.30	2.57
Human	3.47	2.49	4.26	2.89	3.97	2.83	3.91	2.75
Marginal	3.43	2.39	3.61	2.86	3.78	2.76		

Note. M and *SD* represent mean and standard deviation, respectively.

Table 18

Regression results using HME Index as the criterion

Predictor	*b*	*b* 95% CI [LL, UL]	*beta*	*beta* 95% CI [LL, UL]	sr^2	sr^2 95% CI [LL, UL]	*r*	Fit
(Intercept)	1.35**	[1.14, 1.56]						
Political Ideology	0.05*	[0.00, 0.10]	0.11	[0.01, 0.21]	.01	[.00, .04]	.11*	
								R^2 = .012* 95% CI[.00,.04]

Note. A significant *b*-weight indicates the beta-weight and semi-partial correlation are also significant. *b* represents unstandardized regression weights. *beta* indicates the standardized regression weights. sr^2 represents the semi-partial correlation squared. *r* represents the zero-order correlation. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively.
* indicates $p < .05$. ** indicates $p < .01$.

Table 19

Two-way ANCOVA results using Political Ideology as covariate and HMEindex as the criterion

Source	Sum of Squares	*df*	*F*	*p*
Political Ideology	6.43	1	4.641	.049
Journalist	.19	1	.134	.715
News Topic	97.89	2	35.324	<.001
Journalist x News topic	1.59	2	.573	.564
Error	544355	393		

Table 20

Means and standard errors for HMEindex as a function of a 2(journalist) x 3(news topic) design with Political Ideology as a covariate

Journalist	News Topic	*M*	*Standard Error*	*Lower Limit*	*Upper Limit*
Machine	Gun	1.918	.146	1.63	2.21
Human	Gun	1.805	.145	1.52	2.09
Machine	Immigration	.723	.150	.43	1.02
Human	Immigration	.924	.142	.64	1.20
Machine	Environment	1.878	.141	1.60	2.15
Human	Environment	1.924	.143	1.64	2.21

Table 21

Fixed-Effects ANOVA results using age as the criterion

Predictor	Sum of Squares	*df*	Mean Square	*F*	*p*	partial η^2	partial η^2 90% CI [LL, UL]
(Intercept)	69995.22	1	69995.22	368.01	.000		
Journalist	911.42	1	911.42	4.79	.029	.01	[.00, .04]
News Topic	727.21	2	363.61	1.91	.149	.01	[.00, .03]
Journalist x News Topic	588.90	2	294.45	1.55	.214	.01	[.00, .03]
Error	74939.26	394	190.20				

Note. LL and UL represent the lower-limit and upper-limit of the partial η^2 confidence interval, respectively.

Table 22

Means and standard deviations for age as a function of a 2(Journalist) X 3(News Topic) design

	News Topic							
	Gun		Immigration		Environment		Marginal	
Journalist	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Machine	32.82	13.34	35.98	12.27	37.37	13.44	35.43	13.12
Human	38.09	15.47	36.36	14.68	37.25	13.22	37.22	14.42
Marginal	35.47	14.64	36.18	13.54	37.31	13.28		

Note. M and *SD* represent mean and standard deviation, respectively.

Table 23

Fixed-Effects ANOVA results using HMEindex as the criterion

Predictor	Sum of Squares	*df*	Mean Square	*F*	*p*	partial η^2	partial η^2 90% CI [LL, UL]
(Intercept)	75.36	1	75.36	46.14	.000		
Gender	1.64	1	1.64	1.00	.317	.00	[.00, .02]
Error	650.03	398	1.63				

Note. LL and UL represent the lower-limit and upper-limit of the partial η^2 confidence interval, respectively.

Table 24

Descriptive statistics for HMEindex as a function of Gender.

Gender	*M*	*M* 95% CI [LL, UL]	*SD*
Male	1.43	[1.23, 1.62]	1.33
Female	1.64	[1.47, 1.80]	1.23
Other	1.98	[1.14, 2.81]	0.34
Undisclosed	-0.22	[-15.25, 14.82]	1.67

Note. M and *SD* represent mean and standard deviation, respectively. *LL* and *UL* indicate the lower and upper limits of the 95% confidence interval for the mean, respectively. The confidence interval is a plausible range of population means that could have created a sample mean (Cumming, 2014).

Table 25

t-test results for dependent variables with Jounalist as a factor for Research Question 2

Dependent Variable	*N*	*t*	*p*	*d*
Source Credibility	397	1.093	.275	.130
Message Credibility	398	2.139	.033	.366
Trust	398	3.273	.001	.312
Benevolence	398	4.158	.000	.470
Competence	398	2.070	.039	.242
Integrity	398	2.354	.019	.224
Distrust*	391.206	0.008	.993	.001
Malevolence	398	0.850	.396	.100
Incompetence	398	-2.134	.033	-.276
Deceit	398	1.362	.174	.178

*Levene's test for equality of variances showed that the two condition were not equally distributed ($p = .012$).

Table 26

Means and standard deviations per group for t-tests in Research Question 2

	Condition	*N*	*Mean*	*SD*		Condition	*N*	*Mean*	*SD*
Source Credibility	Machine	196	4.737	1.128	Integrity	Machine	197	4.751	0.919
	Human	203	4.867	1.239		Human	203	4.975	0.982
	Total	399	4.802	1.183		Total	400	4.863	0.951
Message Credibility	Machine	197	6.557	1.760	Distrust	Machine	197	3.247	1.018
	Human	203	6.923	1.664		Human	203	3.248	1.199
	Total	400	6.740	1.712		Total	400	3.247	1.108
Trust	Machine	197	4.486	0.942	Malevolence	Machine	197	3.002	1.130
	Human	203	4.798	0.964		Human	203	3.102	1.223
	Total	400	4.642	0.953		Total	400	3.052	1.176
Benevolence	Machine	197	3.766	1.147	Incompetence	Machine	197	3.435	1.267
	Human	203	4.236	1.113		Human	203	3.159	1.315
	Total	400	4.001	1.130		Total	400	3.297	1.291
Competence	Machine	197	4.942	1.201	Deceit	Machine	197	3.305	1.237
	Human	203	5.183	1.135		Human	203	3.483	1.374
	Total	400	5.063	1.168		Total	400	3.394	1.305

Table 27

Factor loadings for EFA in Hypothesis 1

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
ben1	-0.09	-0.01	0.8	0.02	0.02
ben2	0.07	0.06	0.83	-0.07	0
ben3	0.02	-0.05	0.71	0.1	-0.01
comp1	0.09	0.73	0.12	0.12	0.07
comp2	0.1	0.69	0.03	0.17	0.1
comp3	-0.01	0.68	0.12	0.11	0.06
comp4	0.1	0.56	0.16	0.23	0.07
int1	-0.19	0.27	0.22	0.1	0.2
int2	-0.22	0.24	0.36	0.1	0.1
int3	-0.22	0.04	0.42	0.1	0.08
int4	-0.1	0.16	0.52	0.07	0.1
mal1	0.74	-0.02	0.01	-0.05	-0.08
mal2	0.72	-0.06	0.06	-0.06	-0.04
mal3	0.69	-0.04	0.01	0.01	-0.04
incomp1	0.28	-0.53	-0.03	0.03	-0.12
incomp2	0.38	-0.65	0.05	0.04	0
incomp3	0.28	-0.52	-0.05	0.02	-0.06
dect1	0.78	0.01	-0.05	-0.02	-0.05
dect2	0.72	-0.09	-0.04	-0.01	0.05
dect3	0.72	0.07	-0.16	-0.06	0.06
src1	0.04	0.09	-0.01	0.86	-0.03
src2	-0.18	-0.07	0.06	0.71	0.11
src3	-0.11	0	-0.01	0.69	0.15
src4	0.06	0.08	0.03	0.76	-0.03
msg1	-0.04	-0.04	-0.01	0.09	0.83
msg2	0.05	0.03	0.08	-0.05	0.9
msg3	0	0.02	-0.05	0	0.9

Table 28

Cronbach's Alpha (α) and Composite Reliability (CR) of reflective constructs

Reflective Construct	*α*	*CR*
Benevolence	.851	.851
Competence	.927	.927
D.Benevolence	.847	.848
D.Competence	.847	.847
D.Deceit	.864	.869
D.Incomp	.858	.858
D.Integrity	.779	.781
D.Malevolence	.855	.855
Deceit	.830	.830
Fake News	.884	.884
Incompetence	.866	.866
Integrity	.845	.847
Malevolence	.818	.819
Message Credibility	.923	.923
Source Credibility	.908	.908

Table 29

Means, standard deviations, and correlations with confidence intervals of formative constructs within model

Variable	*M*	*SD*	1	2	3
1. d.distrust	0.00	1.00			
2. d.trust	-0.00	1.00	-.40** [-.48, -.32]		
3. distrust	0.00	1.00	.70** [.64, .74]	-.36** [-.44, -.27]	
4. trust	0.00	1.00	-.36** [-.44, -.27]	.42** [.34, .50]	-.64** [-.69, -.57]

Note. M and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

Table 30

Path coefficients, T-statistics, and p-values, and f2 within Testing Theoretical Model with Source Credibility

Paths	*β*	*T-value*	*p*	*f2*
HME -> Fake News	.069	1.857	.063	.010
HME -> M. Credibility	-.142	2.068	.039	.021
PI -> HME	.115	2.163	.031	.012
PI -> distrust	.053	1.111	.267	.005
PI -> S.Credibility	-.088	1.657	.098	.008
D.distrust -> Distrust	.678	16.537	.000	.778
Distrust -> HME	-.073	1.170	.242	.004
M.Cred -> Fake News	-.706	19.109	.000	1.008
S.Cred -> HME	-.173	2.742	.006	.023

Table 31

R2 and R2 for constructs in the Model with Source Credibility

Constructs	*R2*	*R2 adjusted*
HME	.034	.027
Distrust	.489	.487
Fake News	.516	.514
M.Cred	.020	.018
S.Cred	.008	.005

Table 32

Path coefficients, T-statistics, and p-values, and f2 within Testing Theoretical Model with Trust

Paths	*β*	*T-value*	*p*	*f2*
HME -> Fake News	.069	1.816	.069	.010
HME -> M. Credibility	-.142	2.184	.029	.021
PI -> HME	.112	2.019	.044	.011
PI -> distrust	.053	1.109	.267	.005
PI -> Trust	-.119	2.292	.022	.018
D.distrust -> Distrust	.678	16.628	.000	.778
D.trust -> Trust	.418	8.933	.000	.216
Distrust -> HME	-.063	.940	.347	.002
M.Cred -> Fake News	-.706	18.858	.000	1.008
Trust -> HME	-.124	1.808	.071	.009

Table 33

R2 and R2 for constructs in the model with trust

Constructs	*R2*	*R2 adjusted*
HME	.021	.014
Distrust	.489	.487
Fake News	.516	.514
M.Cred	.020	.018
Trust	.191	.187

Table 34

Path coefficients, T-statistics, and p-values, and f2 within the Additional Model

Paths	β	T-value	p	f2
HME -> M. Credibility	-.142	2.073	.038	.020
Machine H. -> Distrust	.037	.985	.325	.003
Machine H. -> Trust	-.148	3.385	.001	.028
PI -> HME	.108	2.110	.035	.012
PI -> Distrust	.048	.963	.336	.004
PI -> Trust	-.134	2.476	.013	.022
D.distrust -> Distrust	.682	16.416	.000	.781
D.trust -> Trust	.409	8.691	.000	.212
Distrust -> Fake News	.204	4.902	.000	.058
M. Credibility -> Fake News	-.516	8.523	.000	.352
Trust -> Fake News	-.152	2.552	.011	.024

Table 35

R2 and R2 for constructs in the Additional Model

Constructs	R2	R2 adjusted
HME	.012	.009
Distrust	.491	.487
Fake News	.576	.573
M.Cred	.020	.018
Trust	.213	.207

Table 36

Variance inflation factors for items in reported models

Item	*VIF*	*Item*	*VIF*
fake1	2.472	d.int2	1.460
fake2	2.027	d.int3	1.773
fake3	2.447	d.mal1	2.281
fake4	2.840	d.mal2	2.146
HMEindex	1.000	d.mal3	1.991
PI	1.000	dect1	2.605
ben1	2.192	dect2	2.122
ben2	2.150	dect3	2.110
ben3	1.939	incomp1	2.123
comp1	4.449	incomp2	2.361
comp2	3.263	incomp3	2.273
comp3	3.607	int1	2.096
comp4	2.494	int2	2.215
d.ben1	1.888	int3	1.553
d.ben2	2.100	int4	1.994
d.ben3	2.249	mal1	2.031
d.comp1	1.964	mal2	2.196
d.comp2	2.077	mal3	1.853
d.comp3	2.097	msg1	3.531
d.dect1	3.486	msg2	3.367
d.dect2	1.702	msg3	3.476
d.dect3	3.166	sc1	3.300
d.incomp1	2.068	sc2	3.434
d.incomp2	2.196	sc3	3.498
d.incomp3	2.196	sc4	2.597
d.int1	1.717		

Table 37

Mean, standard deviations, correlations, and AVE of reflective constructs

Latent Construct		*M*	*SD*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Benevolence	3.971	1.127	**.815**							
(2)	Competence	2.924	1.157	.652	**.866**						
(3)	D. benevolence	3.409	1.060	.432	.239	**.796**					
(4)	D. competence	2.932	.9705	.415	.365	.570	**.807**				
(5)	D. Deceit	3.719	1.449	-.270	-.177	-.324	-.251	**.824**			
(6)	Distrusting stance	3.428	1.145	-.181	-.052	-.417	-.176	.407	**.734**		
(7)	Deceit	4.499	1.326	-.379	-.388	-.276	-.277	.803	.388	**.808**	
(8)	D. incompetence	3.963	1.352	-.303	-.266	-.307	-.335	.919	.438	.734	**.821**
(9)	D. integrity	3.497	1.008	.472	.306	.875	.685	-.352	-.411	-.350	-.330
(10)	D. malevolence	4.029	1.339	-.268	-.230	-.278	-.236	.983	.437	.807	.956
(11)	Fake news perception	5.342	1.057	.392	.577	.193	.206	-.275	-.185	-.534	-.319
(12)	Machine Heuristic	4.067	.4190	.262	.200	.091	.045	.063	-.001	.102	.036
(13)	Incompetence	4.613	1.275	-.473	-.721	-.145	-.227	.451	.268	.743	.536
(14)	Integrity	3.146	.9440	.810	.872	.392	.491	-.332	-.169	-.602	-.384
(15)	Political ideology	4.013	1.796	.107	.035	.100	.065	-.057	-.042	-.017	-.037
(16)	Hostile media effect	5.978	1.415	-.081	-.053	-.040	.012	.093	.073	.157	.075
(17)	Malevolence	4.840	1.193	-.282	-.411	-.226	-.226	.603	.344	.933	.655
(18)	Message credibility	6.763	1.673	.445	.661	.157	.241	-.136	-.094	-.373	-.197
(19)	Source credibility	4.821	1.135	.569	.776	.211	.303	-.191	-.088	-.413	-.239
(20)	Selective categorization	6.660	1.950	-.052	.072	-.024	.011	-.105	-.036	-.047	-.105
(21)	Trusting stance	3.207	1.278	.322	.185	.636	.478	-.216	-.619	-.223	-.228

(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)

(9)	**.732**												
(10)	-.283	**.810**											
(11)	.248	-.347	**.798**										
(12)	.049	.007	.114	**1.000**									
(13)	-.215	.528	-.606	-.088	**.818**								
(14)	.489	-.396	.702	.201	-.703	**.768**							
(15)	.120	-.003	.065	.040	-.033	.074	**1.000**						
(16)	-.077	.062	-.122	.046	.105	-.114	-.220	**.630**					
(17)	-.241	.711	-.590	.077	.744	-.596	-.010	.197	**.787**				
(18)	.232	-.197	.748	.125	-.566	.663	.085	-.101	-.402	**.892**			
(19)	.264	-.232	.697	.132	-.630	.773	.038	-.129	-.426	.747	**.844**		
(20)	-.023	-.095	.049	.047	-.137	.007	-.166	.459	-.039	.101	.065	**.743**	
(21)	.619	-.185	.132	.081	-.179	.294	.072	-.025	-.163	.105	.180	-.084	**.830**

Note. The AVE values are shown in the diagonal in bold. "D." is an abbreviation of "Disposition to."

**Single item was loaded for the construct*

Appendix D. Figures

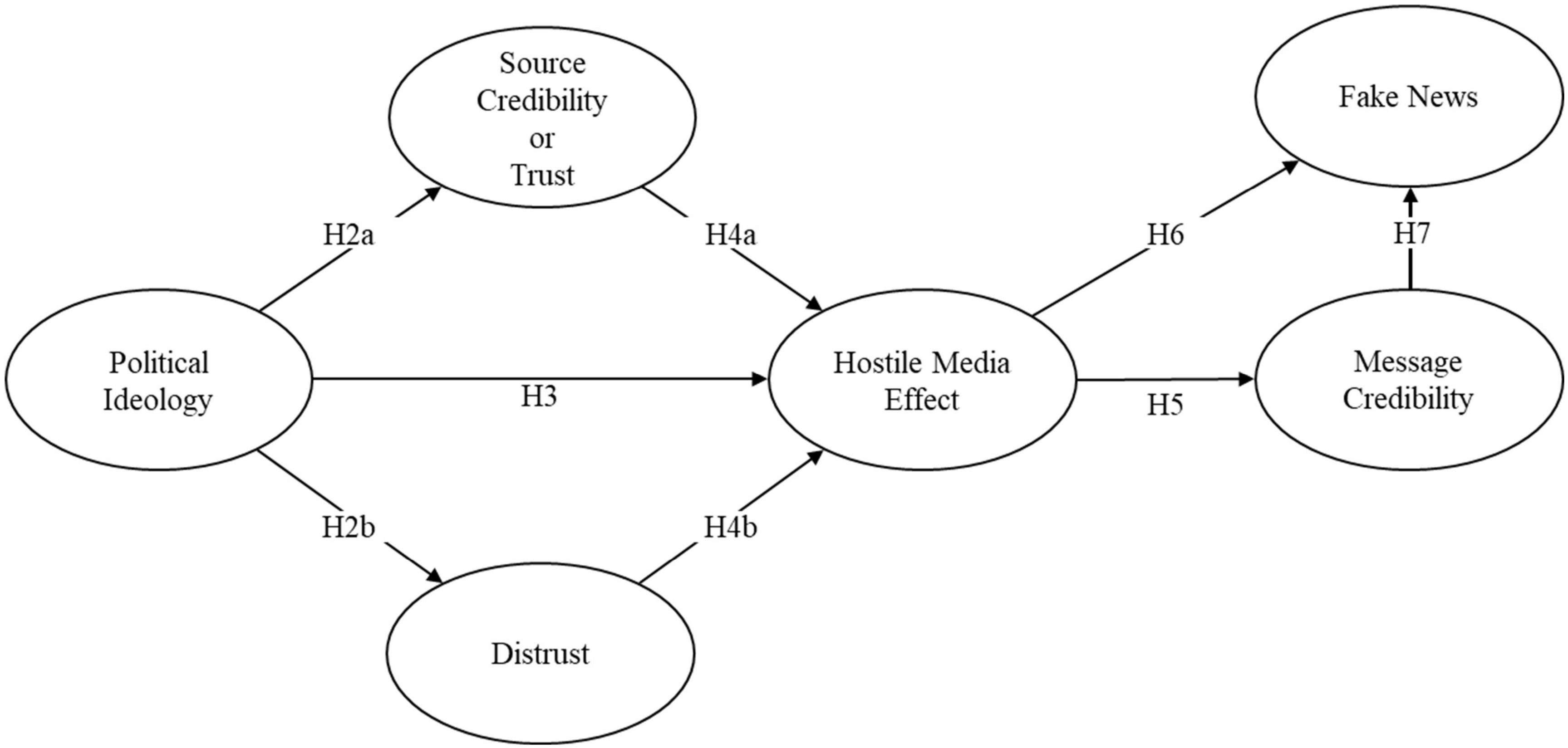

Figure 1. Theoretical model.

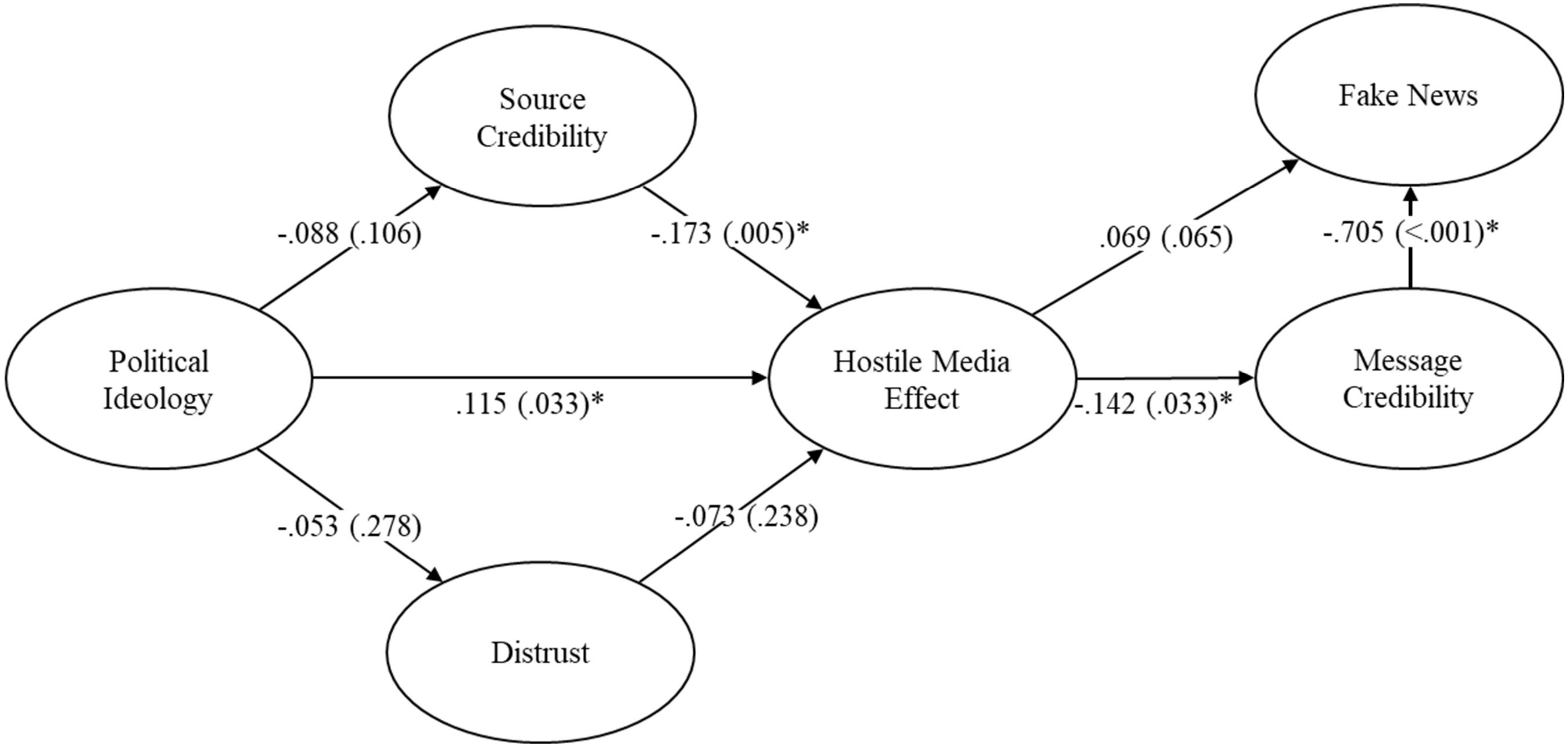

Figure 3. Hypothesis testing using Trust. Path coefficients (β) and *p*-values are shown.

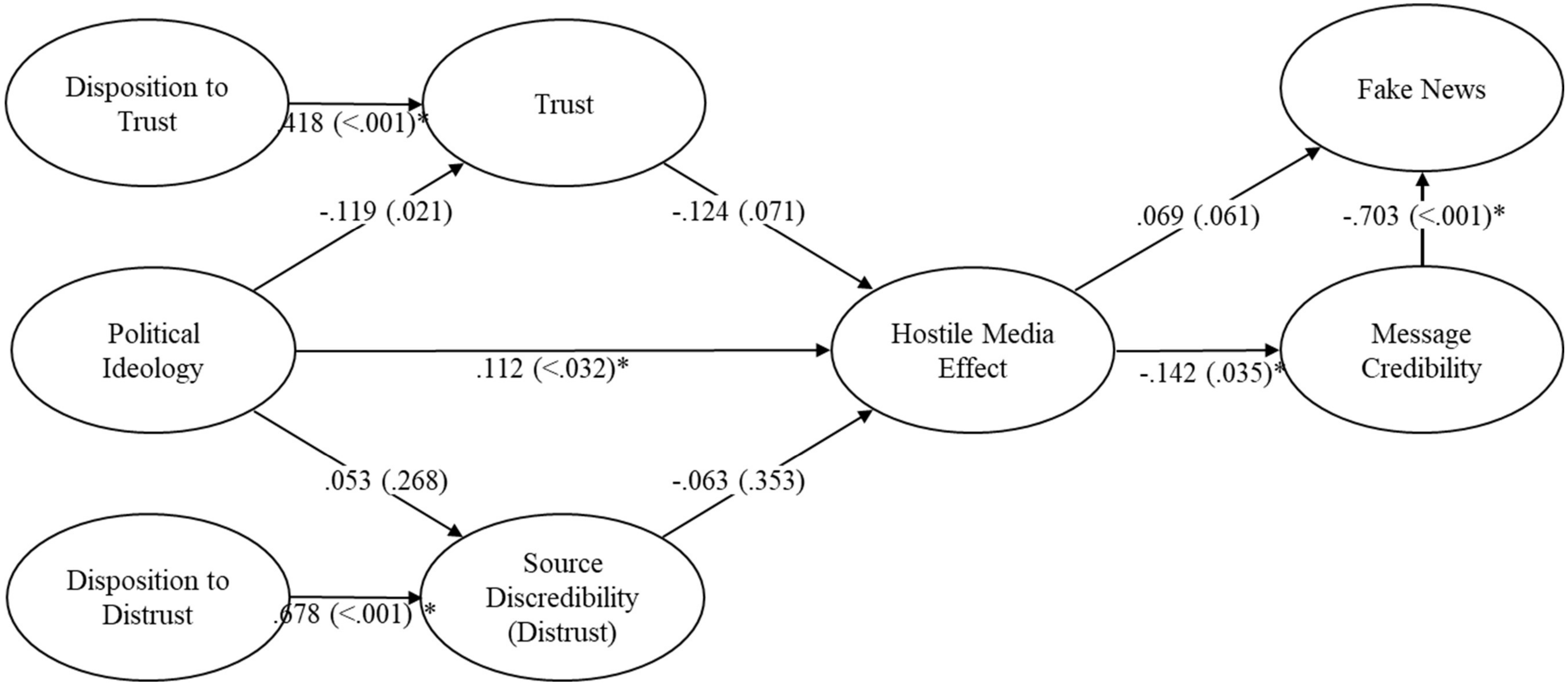

Figure 4. Hypothesis testing using Trust. Path coefficients (β) and *p*-values are shown.

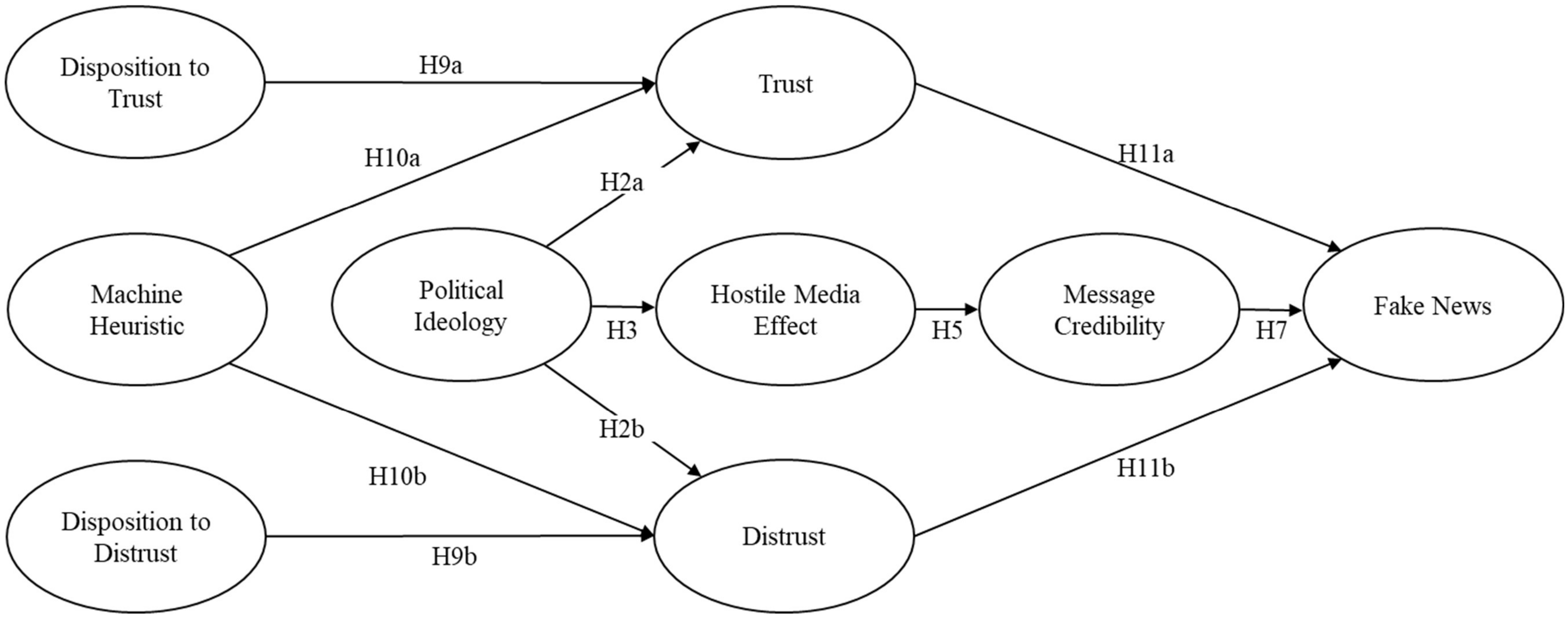

Figure 5. Additional Model. Path coefficients (β) and *p*-values are shown.

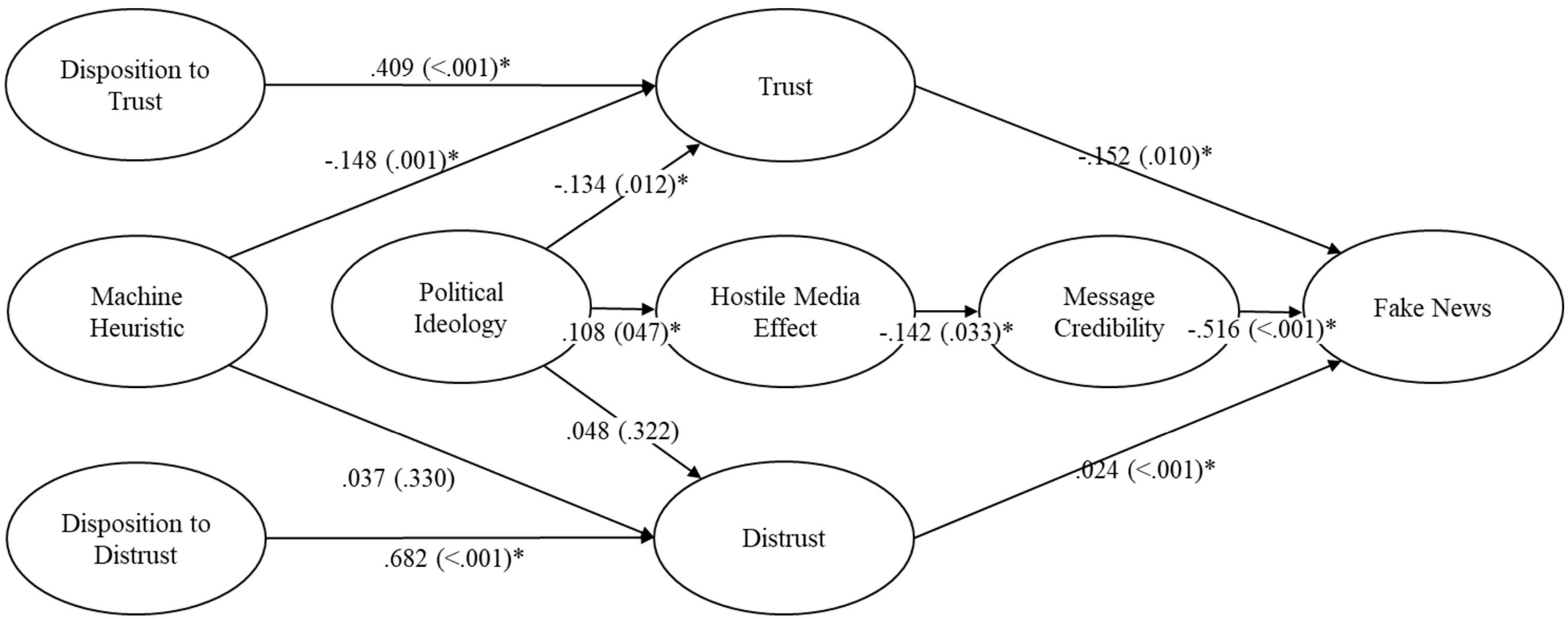

Figure 6. Addition Model testing. Path coefficients (β) and *p*-values are shown.

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O_LD-
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EDUCATION

Syracuse University, Syracuse, NY
PhD, Public Communication, Expected December 2019

- Dissertation: "*The Dark Side of Credibility: An Exploratory Study on Trust, Distrust, and Credibility in Machine Journalism*"
- Committee: Makana Chock (Advisor), Frank Biocca, Greg Munno, and Dennis Kinsey

Syracuse University, Syracuse, NY
MA, Media Studies, 2013

Chung-Ang University, Seoul, Korea
BA, Mass Media and Journalism

TEACHING AND RESEARCH INTERESTS

Video Game and Interactive Media
Human-Computer Interaction
Virtual Reality and Augmented Reality
Psychophysiology and Neuropsychology
Media Psychology
Quantitative Research Method
Communication and Society
Health Communication

PUBLICATIONS

- Shin, M., **Song, S. W.**, Kim, S. J., & Biocca, F. (2019). The effects of 3D sound in a 360-degree live concert video on social presence, parasocial interaction, enjoyment, and intent of financial supportive action. *International Journal of Human-Computer Studies,* 126, 81-93. doi:https://doi.org/10.1016/j.ijhcs.2019.02.001
- Shin, M., **Song, S. W.**, & Chock, T. M. (2019). Uncanny Valley Effects on Friendship Decisions in Virtual Social Networking Service. *Cyberpsychology, Behavior, and Social Networking*, *22*(11), 700-705. doi: https://doi.org/10.1089/cyber.2019.0122

CONFERENCE PRESENTATIONS & PROCEEDINGS

- Shin, M., **Song, S. W.** (2019 May). *Your avatar seems too uncanny to accept your friend request: The role of uncanny valley effects on perceived humanness, perceived trustworthiness, and the likelihood of friendship with an unacquainted user in virtual social networking services.* Paper to be presented at the International Communication Association, Washington, DC.
- **Song, S. W.**, Shin, M., Cho, Y., & Kim, S. (2017, May). *What makes a virtual concert more realistic: Spatialized 3D sound with head tracking function in a multimodal virtual reality system.* Paper presented at the International Communication Association, San Diego, CA.

- Bandara, D., **Song, S.**, Hirshfield, L., & Velipasalar, S. (2016). A more complete picture of emotion using electrocardiogram and electrodermal activity to complement cognitive data. In D. D. Schmorrow & C. M. Fidopiastis (Eds.), *Foundations of Augmented Cognition: Neuroergonomics and Operational Neuroscience: 10th International Conference, AC 2016, Held as Part of HCI International 2016, Toronto, ON, Canada, July 17-22, 2016, Proceedings, Part I* (pp. 287-298). Cham: Springer International Publishing.
- Shin, M., **Song, S. W.**, Biocca, F., Cho, Y., & Yang, H. (2016, May). *Effects of reverberation and SPL on social presence and parasocial relationships: Why do people prefer live music to recorded music?* Paper presented at the International Communication Association, Fukuoka, Japan.
- **Song, S. W.**, & Finnerty, A. (2013, March). *Public and private issue conflicts in U.S. television shows.* Paper presented at the Popular Culture Association, Washington, DC.

RESEARCH EXPERIENCE

- Research Associate, Kwangoon University, Seoul Korea (2019)
- Research Assistant, contributed on ARPA-E grant application at Syracuse University (2017).
- Research Assistant, supported preparation of Dr. Biocca's presentation at Amazon (2017).
- Research Assistant, Lab manager for M.I.N.D. Lab at Syracuse University (2014-2015).
    - Established and maintained setting for fNIRS and psychophysiology data collection
    - Coordinated lab facility establishment at a new venue in downtown Syracuse
- Research Assistant, intern for M.I.N.D. Lab at Syracuse University (2012-2013).
    - Restored and equipment settings for psychophysiology data collection and analysis

TEACHING EXPERIENCE

- Guest Lecture, Artificial Intelligence and Society, at Kwangoon University, Seoul Korea (Fall 2019)
- Instructor, *Communications and Society*, received 3.9/5.0 average rating for class meeting effectiveness from student survey (Spring 2015).
- Guest Lecturer, *Methods in the M.I.N.D. Lab*, led seminar on psychophysiology at doctoral level (Fall 2015).
- Guest Lecturer, *Human-Computer Interaction*, instructed usability testing (Fall 2015 and Fall 2016).
- Teaching Assistant, *Communications and Society* (Summer 2014 and Fall 2014).

SERVICE

- Research Assistant, performed research for the relaunch project for the Executive Master's Degree program in Communication Management at Newhouse (Summer 2016).
- Vice President, Korean Student Association of Syracuse University (2012-2014).

SKILLS

- Proficient in statistical analysis and software (R, SPSS, LISREL, and NIRS SPM via MATLAB).
- Proficient in psychophysiological and neuroimaging apparatus and analysis (Biopac/Acqknowledge, Hitachi ETG-4000 fNIRS).
- Proficient in usability testing tools (e.g., Gazepoint eye-tracker, Axure, and MORAE)
- Working knowledge on data mining using Python.

LANGUAGES

English (Native), Korean (Native), Japanese (working proficiency for general communication)