International Journal of Communication 15(2021), 3760–3781 1932–8036/20210005

Source Credibility Matters: Does Automated Journalism Inspire Selective Exposure?

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To examine whether selective exposure occurs when people read news attributed to an algorithm author, this study conducted a 2 (author attribution: human or algorithm) × 3 (article attitude: attitude-consistent news, attitude-challenging news, or neutral story) × 2 (article topic: gun control or abortion) mixed-design online experiment (N = 351). By experimentally manipulating the attribution of authorship, this study found that selective exposure and selective avoidance were practiced when the news article was declared to be written by algorithms. Results revealed that people were more likely to select attitude-consistent news rather than attitude-challenging news and rated attitude consistent news stories as more credible than attitude challenging news for stories purportedly written by both algorithms and human journalists. For attitude-consistent gun-rights stories, people were more likely to expose themselves to human attribution stories rather than algorithmic attribution stories. Results also showed that source credibility partially mediated the influence of issue partisanship on selective exposure for gun stories. This study bears implications on the selective exposure theory and the emerging field of automated journalism.

Keywords: automated journalism, algorithm, message credibility, selective avoidance, selective exposure, source credibility

Recent years have witnessed media organizations' adoption of AI and automation in the production and consumption processes (Napoli, 2014; Thurman, Dörr, & Kunert, 2017; S. Wu, Tandoc, & Salmon, 2019). With advanced natural language processing and machine learning techniques, algorithms are ubiquitous in the contemporary media environment such as algorithmic content moderation (Gorwa, Binns, & Katzenbach, 2020), misinformation detection algorithms (e.g., Rasool, Butt, Shaukat, & Akram, 2019), automated journalism (Carlson, 2015; Haim & Graefe, 2017), and news ranking algorithms (Bakshy, Messing, & Adamic, 2015). Among these technologies, automated journalism is a new form of news production in which news can be automatically generated by algorithms without human intervention beyond the initial development of algorithms (Carlson, 2015; Haim & Graefe, 2017; Napoli, 2014). An increasing number of major newsrooms around the world have adopted automation technology to generate news

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Date submitted: 2020-09-26

stories (Tandoc, Yao, & Wu, 2020). Even though automated journalism is mostly limited to fact-based news with routine topics such as sports and financial news (e.g., Carlson, 2015; Haim & Graefe, 2017; Napoli, 2014), many researchers and practitioners have reached a consensus that automated journalistic writing can go beyond these domains (Y. Wu, 2020). For instance, Chinese state-run media Xinhua News Agency began to automate political news since 2018 such as coverage of the National People's Congress (Jia, 2020). Many researchers have also examined automated news in the political context (e.g., Caswell & Dörr, 2018; R. Liu, Jia, & Vosoughi, 2021; Melin et al., 2018; Waddell, 2018, 2019; Y. Wu, 2020).

Previous studies have examined how machine or human author attribution will affect people's perceptions of news stories such as perceived bias and credibility (Jung, Song, Kim, Im, & Oh, 2017; Tandoc et al., 2020; Waddell, 2019). One recent study found that political news stories were perceived as less biased among automated news stories compared with human-written news possibly because people tend to believe stories written by a machine would be objective and free from political bias (Y. Wu, 2020). Wang (2021) found that news moderated by a machine as opposed to a human agent was rated as less biased because people regard algorithmic cues as unbiased and neutral. Another pioneering work found that algorithmic author attribution reduces message credibility through the indirect pathway of perceived bias (Waddell, 2019). Those studies provide initial evidence that the machine heuristic may reduce the perceived bias of political news, which offers possible optimism that introducing automation services may be capable of increasing partisans' exposure to cross-cutting information and reducing selective exposure to ideologically consistent information.

Selective exposure and *selective avoidance* studies suggest that readers prefer attitude-consistent information and tend to avoid attitude-challenging information (Chaffee, Saphir, Grap, Sandvig, & Hahn, 2001; Donsbach, 1991), but some people also seek information that challenges their beliefs (Knobloch-Westerwick & Meng, 2009). One explanation for the occurrence of selective exposure is that people make information selections based on their judgments about informational credibility and quality (N. J. Stroud, 2017). People prefer highly credible information, and conversely, they tend to believe information that supports their beliefs to be more credible and of higher quality (Fischer, Schulz-Hardt, & Frey, 2008). Credibility judgement of news stories is often affected by different heuristics such as author's reputation, site design, and writing tone (Bulkow, Urban, & Schweiger, 2013; Hovland, Janis, & Kelley, 1953; McCombs & Stroud, 2014; Metzger & Flanagin, 2015; Pingree & Stoycheff, 2013).

As technology diffuses, the importance of source cues to news exposure grows because consumers are increasingly customizing their online news menus (Iyengar & Hahn, 2009). As the number of media using algorithms to automate news increases, algorithmic authorship becomes a novel source cue that remains underexplored. In terms of the credibility of algorithmic sources, some scholars argue that AI is often perceived as fair, objective, unbiased, and with less political agenda (Gillespie, 2014). People tend to have common stereotypes about machine cues wherein people consider machines as mechanical, objective, and ideologically unbiased (Sundar & Kim, 2019). However, whether the assumption of machine objectivity and neutrality is reflected in public beliefs remains unknown. In fact, one recent meta-analysis including 12 studies on automated news shows that news attributed to algorithms is perceived as slightly less credible than news attributed to humans, but the difference is small (Graefe & Bohlken, 2020). Adding to previous literature, this current study focuses on the source credibility (algorithmic author versus human author) and further examines whether algorithmic source attribution affects the selection process of political news stories.

Therefore, this study conducted an online experiment (*N* = 351) to manipulate the author attribution of news stories, aiming to fill in the gap by examining whether selective exposure will occur when people read news attributed to an automated author. More specifically, this study examined the following overarching questions: Will readers practice selective exposure if the attributed author is an algorithm? If so, does this selective exposure come from news consumers' evaluations of credibility of the automated source?

Literature Review

Automated Journalism

An increasing number of news organizations all over the world have adopted automation technology to generate news. Automated journalism refers to a new type of media production where news can be automatically generated by algorithms on a large scale with little human intervention beyond the initial programming (Carlson, 2015; Haim & Graefe, 2017). Scholars also use automated news or machine-written news to specifically refer to news content created by algorithms (Thurman et al., 2017; Waddell, 2019). To better understand how this new technology shapes audiences' news consumption process, researchers examine readers' perception of automated journalism by conducting various empirical studies (e.g., Clerwall, 2014; Haim & Graefe, 2017; Waddell, 2019).

Empirical research on readers' perception of automated journalism can be categorized into two major types (B. Liu & Wei, 2019). The first type examines actual content of news generated by algorithms (e.g., *Los Angeles Times*' Quakebot; Clerwall, 2014; Graefe, 2016; Haim & Graefe, 2017; Jia & Gwizdka, 2020; van der Kaa & Krahmer, 2014; Y. Wu, 2020). While some studies suggest that automated news was rated slightly more credible when participants read both types of news (Graefe, Haim, Haarmann, & Brosius, 2018; Haim & Graefe, 2017), others found that there's no difference in credibility between automated and human-written news (Clerwall, 2014; Jia, 2020; van der Kaa & Krahmer, 2014). Studies that examine actual content produced by machines as opposed to humans have certain limitations. Although scholars try to control for topics and lengths, it is not easy to identify comparable human-written and automated news content due to the unbalanced number of human-written and automated stories, especially in the political context. Also, studies following this approach may confound the effect of news content and that of news source when combining both (B. Liu & Wei, 2019). Such limitations may lead to mixed results of previous studies on comparison between automated and human-written news content.

The second type of automated journalism study focuses exclusively on the effects of machine source attribution instead of the content variance (e.g., Jung et al, 2017; Tandoc et al., 2020; Waddell, 2019). Findings reveal that manipulating the algorithm's authorship through experimental research does affect reader's perceptions of article quality (Jung et al., 2017). The second type of research also yields mixed findings. Some studies found no main difference in the perceived source credibility between news attributed to algorithmic and human authors (e.g., Tandoc et al., 2020). Some found that machine authorship enhances news credibility more prominently than human authorship does, especially in news that requires more information processing because people's prior expectations of machine authors is lower than that of human authors for interpretive news (B. Liu & Wei, 2019). Other studies suggest that news attributed to humans is perceived as more credible than news attributed to algorithms (Waddell, 2019). One meta-analysis concludes that news attributed to humans is rated somewhat higher than news attributed to algorithms, yet the difference is small (Graefe & Bohlken, 2020). Very few studies, however, have further investigated whether the manipulation of source attribution (human versus algorithm) will affect selective exposure in the political context. Therefore, this study focuses on source credibility of human versus algorithmic authors, aiming to fill in the gap by linking selective exposure with credibility of news attributed to algorithmic sources.

Selective Exposure

Selective exposure refers to the phenomenon that individuals are often systematically motivated to select attitude-consistent messages that are congenial with their beliefs, attitudes, or decisions. In contrast, *selective avoidance* refers to the fact that individuals often avoid attitude-challenging messages (Fischer, Jonas, Frey, & Schulz-Hardt, 2005; N. Stroud, 2011). Previous studies have revealed that selective exposure occurs in many contexts. Some studies examine whether selective exposure exists when people are exposed to different political topics, such as gun control, abortion, immigration, and gay marriage (Knobloch-Westerwick, Mothes, & Polavin, 2017; Wojcieszak, 2019). Other studies have examined whether selective exposure works on different message channels, including newspaper, radio, cable news, and social media such as Facebook and blogs (Johnson, Bichard, & Zhang, 2009; Metzger & Chaffee, 2001). Studies on partisan selective exposure often take place in polarized countries such as the United States. Researchers have found that Americans are more polarized and more likely to practice selective exposure (Fletcher, Cornia, & Nielsen, 2020; Urman, 2020). Americans may practice selective exposure more than those in other countries not only because of their two-party system (Urman, 2020) but also because the United States features an increasingly strong digital market with high choice media (Iyengar & Hahn, 2009).

While earlier scholars mainly focus on selective exposure in the context of news topics and media outlets, recent studies examined how the source bias and content bias affect selective exposure to online information (Fletcher & Park, 2017; Pearson & Knobloch-Westerwick, 2018; Westerwick, Johnson, & Knobloch-Westerwick, 2017). Results show that individuals are more likely to select messages that agree with their political views regardless of the source (Knobloch-Westerwick, Mothes, Johnson, Westerwick, & Donsbach, 2015; Westerwick et al., 2017). Those results suggest that individuals may choose stories that support their political views regardless of whether they are written by humans or algorithms. Therefore, the following hypotheses were proposed:

H1a: *Readers will be more likely to select attitude-consistent news rather than attitude-challenging news for stories purportedly written by both algorithms and humans.*

H1b: *Readers will be more likely to avoid attitude-challenging news rather than attitude-consistent news for stories purportedly written by both algorithms and humans.*

Source and Message Credibility

Credibility research harkens back to the post–World War II era when researchers began to investigate how characteristics of speakers and their messages influenced their persuasive abilities (Hovland et al., 1953). Early research by the Yale group determined that speaker expertise, their qualifications or ability to know the truth, and truthfulness, their motivation to tell the truth, were the major determinates of source credibility (Hovland et al., 1953). In general, messages that are well organized (Gass & Seiter, 1999), well written and interesting (McCroskey, 1966; Slater et al., 1997), accurate, comprehensive, current, reliable, and valid (Rieh & Belkin, 1988), as well as rely on facts rather than opinions (Hamilton & Hunter, 1998) are judged as more credible. Later research extends the concept of source beyond individual speakers to include media and nonmedia organizations. Specifically, media studies examined the differences between media sources (e.g., newspaper and television; Carter & Greenberg, 1965; Greenberg, 1966), online versus offline media (Abdulla, Garrison, Salwen, Driscoll, & Casey, 2004; Flanagin & Metzger, 2000), and user-generated versus traditionally delivered sources (Johnson & Kaye, 2004, 2014). As the concept of source extended beyond individuals to include organizations, how source credibility was measured also evolved. While there is no agreed-on measure of credibility, believability, fairness, accuracy, and depth of information have been identified as credibility elements by several researchers (Gaziano & McGrath, 1986; Metzger, Flanagin, Eyal, Lemus, & McCann, 2003; Newhagen & Nass, 1989).

Automated Journalism, Selective Exposure, and Credibility

Research from both media credibility and selective exposure scholars suggests these two concepts are closely linked. Credibility studies have discovered that credibility increases when there are few discrepancies between the views of the speaker and the receiver (Hamilton, 1988) because messages that support the receiver’s attitudes are perceived as less biased (Stamm & Dube, 1994). Similarly, one standard that individuals use to judge message credibility of a statement is self-confirmation. Individuals judge information that supports their beliefs as credible and discredit information that challenges their beliefs no matter how well argued or researched that information is (Metzger & Flanagin, 2015; Sundar, 2008). Prior studies show that individuals often selectively expose themselves to information from sources they perceive as unbiased and highly credible (Knobloch-Westerwick et al., 2015; Metzger, Hartsell, & Flanagin, 2015; Westerwick et al., 2017). For instance, news from traditional media is typically judged as more credible than partisan sources because audiences employ journalistic values such as fairness and balance in assessing credibility (Johnson & Kaye, 2013, 2014; Yamamoto, Lee, & Ran, 2016).

While credibility research has extended from individuals to organizations and message platforms, a basic assumption is that the messages were produced by humans. This no longer holds true. With the advent of automated journalism, news now can be automatically generated by algorithms (Carlson, 2015; Napoli, 2014). Past work provides initial evidence that news attributed to human is perceived as slightly more credible than news attributed to algorithms, even though the difference is small (Graefe & Bohlken, 2020; Waddell, 2019). Adding to prior work, this study hypothesized that people would be more likely to select news attributed to human authors because they consider human authors as more credible than algorithmic authors. Therefore, this study predicted the following hypotheses:

H2: Readers will be more likely to select attitude-consistent stories purportedly written by humans rather than attitude-consistent stories purportedly written by algorithms.

H3: Readers will rate attitude-consistent news stories as more credible than attitude-challenging news for stories purportedly written by both algorithms and humans.

H4: Readers will perceive human sources as more credible than algorithms sources.

H5: Readers will perceive news stories attributed to human authors as more credible than news stories attributed to algorithmic authors.

One study found that algorithmic author attribution reduced message credibility through an indirect pathway of perceived bias (Waddell, 2019). Another study found that trust in source played a mediating role in perceptions of algorithmic products (Shin, 2020). Adding to past work, this study predicted a mediating effect of source credibility in the selective exposure process.

H6: Source credibility will mediate the influence of issue partisanship on selective exposure.

Method

Experimental Design

The present study adopted a 2 (author attribution: human or algorithm) × 3 (article attitude: attitude-consistent news, attitude-challenging news, or neutral story) × 2 (article topic: gun control or abortion) mixed-factorial design. An online experiment (N = 351) was conducted in 2019 to experimentally manipulate the attribution of authorship. Author attribution is a between-subjects variable. Participants were randomly assigned to read articles either purportedly written by humans (n = 189) or algorithms (n = 162). Article attitude and topic are within-subjects variables. Each participant was asked to read three articles for each topic to test robustness.

Procedures

Before the experiment, participants were asked to report their political ideologies, party affiliations, and attitudes toward gun and abortion issues. Participants answered several questions about source credibility for both human authors and algorithmic authors. Then, participants were randomly assigned to read six articles either purportedly written by humans or algorithms. During the experiment, before reading each story, participants were informed of the listed author(s) of the story they were about to read. Participants were informed that "the following news story you are about to read is written by a human staff reporter, Jim Richard" or "the following news story you are about to read is automatically generated by an algorithm named Automated Insights." After participants read each article, they were asked to rate selective exposure and selective avoidance questions on 7-point scales. They were also asked to rate the credibility of the story they just read. Given the important role of author attribution in this experimental design, participants were asked whether they could recall the author listed on the byline with options "Automated Insight," "staff reporter Jim Richard," and "I don't remember" after all dependent measures (adapted from Waddell, 2019).

Participants

For both the pretest and the main experiment, participants from the United States were recruited from Amazon Mechanical Turk (MTurk). MTurk is an online crowdsourcing platform for data collection with a diverse population of self-selected participants (M. Buhrmester, Kwang, & Gosling, 2011; Paolacci, Chander, & Ipeirotis, 2010). Participants in both pretest and main experiment were paid $0.80 for their participation. The researchers conducted a prior power analysis for the main experiment to estimate the total sample size. A priori power analysis indicated that a minimum of 327 participants would be needed. Two attention checks were used throughout the pretest and the main experiment to exclude careless responding.[1] Participants were randomly assigned to read articles either purportedly written by humans or algorithms. After ruling out subjects younger than 18 (n = 1), repeated IP addresses (n = 9), the incomplete answers (n = 250), and subjects who failed both attention checks (n = 4), 351 participants remained. Detailed descriptive statistics of pretest and main experiment participants can be found in Table 1.

Table 1. Descriptive Statistics of Participants in Pretest and Main Experiment.

	Pretest	Main experiment
N	55	351
Age		
M	34.03	41.13
SD	10.81	12.49
Gender		
Male (%)	69.09	53.85
Education		
M	15.85	15.70
SD	2.07	2.41
Race		
White (%)	69.09	75.2
Asian (%)	20	8
Black (%)	0	8
Latino (%)	7.27	4
Others (%)	3.63	4.8

Stimuli

To avoid any possible bias brought by the media source (i.e., Fox or MSNBC), this study used Photoshop to make every stimulus looks like a screenshot from the same fictional news site. The bylines of articles were on the left side of the fake screenshot, followed by published time and three social media

[1] To pass the attention check, participants needed to answer two simple questions about two stories.

sharing buttons. In the byline, it either shows "by Automated Insights" or "by staff reporter Jim Richard." "Automated Insights" is an algorithm provider that can automatically generate news content that publishes millions of articles on topics such as sports, finance, and marketing for diverse news outlets (Anderson, 2013; Cohen, Hamilton, & Turner, 2011; Ulanoff, 2014).

Gun control and abortion haven been selected by many previous researchers as their stimuli topics (e.g., Kim, 2007; King, Schneer, & White, 2017) because they are two of the most controversial sociopolitical issues in the United States (Wojcieszak, 2019). For the gun control topic, three stimuli were selected with different political attitudes, respectively pro-gun rights, neutral, and pro-gun control. For the abortion topic, three articles were respectively pro-life, neutral, and pro-choice. Stories were selected from Fox News, Bloomberg, *The New York Times*, and the Associated Press. The original media outlet information was removed. Each story was edited to about 250 words by two researchers. Stories were shown in a random order.

Pretest

A pretest on MTurk was conducted among participants (N = 55) to test whether selected stories were ideologically biased in the predicted direction. After removing repeated IP address (n = 1), people who did not complete the survey (n = 23), and people who failed both attention checks (n = 2), the sample size of participants in the pretest was 55. Participants were asked to read six articles from two topics. After reading each story, they need to answer the question "how biased do you think this story is?" on a 7-point scale. Several sample t tests were conducted to test whether the stimuli were biased in the direction they were designed to be. The pretest was successful, as polarized articles were statistically different from the neutral point (4, p < .01), and neutral stories were not.

Measurements

Before reading stories, participants were asked for their issue attitudes about gun control and abortion, and source credibility. Selective exposure and selective avoidance were assessed by a question after participant read each article, "on a scale of 1 to 7, with 1 indicating '*not at all likely*' to 7 indicating '*extremely likely*,' how likely are you to purposely click (avoid) on or connect to this article in the future?" (adapted from Johnson & Kaye, 2013; Metzger et al., 2015). Although this was not a direct behavioral measure, self-reported behavioral intention has proven to be a reliable predicator of actual behavior of news selection (Metzger et al., 2015; Sheeran, 2002). Credibility was measured as an index consisting of believability, fairness, accuracy, depth of information, and authenticity on five 7-point scales, with authenticity items recoded. Five items were highly correlated, Cronbach's α = .88 (adapted from Metzger et al., 2003). After all dependent measures, participants were asked if they could recall the author listed on the byline (adapted from Waddell, 2019).

Manipulation Check

To ensure the experimental manipulation was effective, participants answered a manipulation check to rate their perceived source anthropomorphism of the listed author(s) on a 7-point scale consisting of four semantic differential items "fake/natural," "unconscious/conscious," "artificial/life-like," and "mechanical/organic" (adapted from Airenti, 2015). The four items were highly correlated and can be averaged to form a reliable index (M = 4.99, SD = 1.58, Cronbach's α = .94). A one-way analysis of variance (ANOVA) was conducted to compare the difference of the perceived source anthropomorphism between the two groups. The source anthropomorphism (M = 3.89, SD = 1.62) rated by participants (n = 162) who were assigned to the algorithm group was significantly lower than the source anthropomorphism (M = 5.44, SD =1.17) rated by participants (n = 189) who were assigned to the human group, $F(1, 349) = 106.37$, $p < .001$, which showed the manipulation was successful.

Results

Multivariate analyses of variance (MANOVAs) were conducted to test H1, H2, and H3. H1a predicted that readers would be more likely to select attitude-consistent news rather than attitude-challenging news for stories purportedly written by both algorithms and humans. For the gun topic, there was a statistically significant difference in selective exposure scores for both pro-gun-rights stories, $F(1, 350) = 84.44$, $p < .001$, and pro-gun-control stories, $F(1, 350) = 45.05$, $p < .001$, based on participants' original gun issue attitude, Wilks' $\Lambda = .61$, $\eta^2 = .39$. For both human and algorithmic attribution stories, the directions were as we expected, as people were more likely to view attitude-consistent stories. For the abortion topic, there was a statistically significant difference in selective exposure for pro-life stories, $F(1, 350) = 53.18$, $p < .001$, and pro-choice stories, $F(1, 350) = 10.84$, $p < .001$, based on participants' original abortion issue attitude, Wilks' $\Lambda = .72$, $\eta^2 = .28$. For both human and algorithmic attribution stories, the directions of selective exposure to abortion stories were as we expected. Therefore, H1a was fully supported.

H1b predicted that readers would be more likely to avoid attitude-challenging news rather than attitude-consistent news for stories purportedly written by both algorithms and humans. For the gun topic, there was a statistically significant difference in selective avoidance scores for pro-gun-rights stories, $F(1, 350) = 66.72$, $p < .001$, and pro-gun-control stories, $F(1, 350) = 49.13$, $p < .001$, based on participants' original gun issue attitude, Wilks' $\Lambda = .69$, $\eta^2 = .32$. For both human and algorithmic attribution stories, the directions were as we expected. For the abortion topic, there was a statistically significant difference in selective avoidance for pro-life stories, $F(1, 350) = 8.96$, $p = .003$, and pro-choice stories, $F(1, 350) = 63.42$, $p < .001$, based on participants' original abortion issue attitude, Wilks' $\Lambda = .70$, $\eta^2 = .30$. H1b was fully supported. For both human and algorithmic attribution stories, the directions were as we expected. Therefore, H1 was fully supported, as shown in Figure 1.

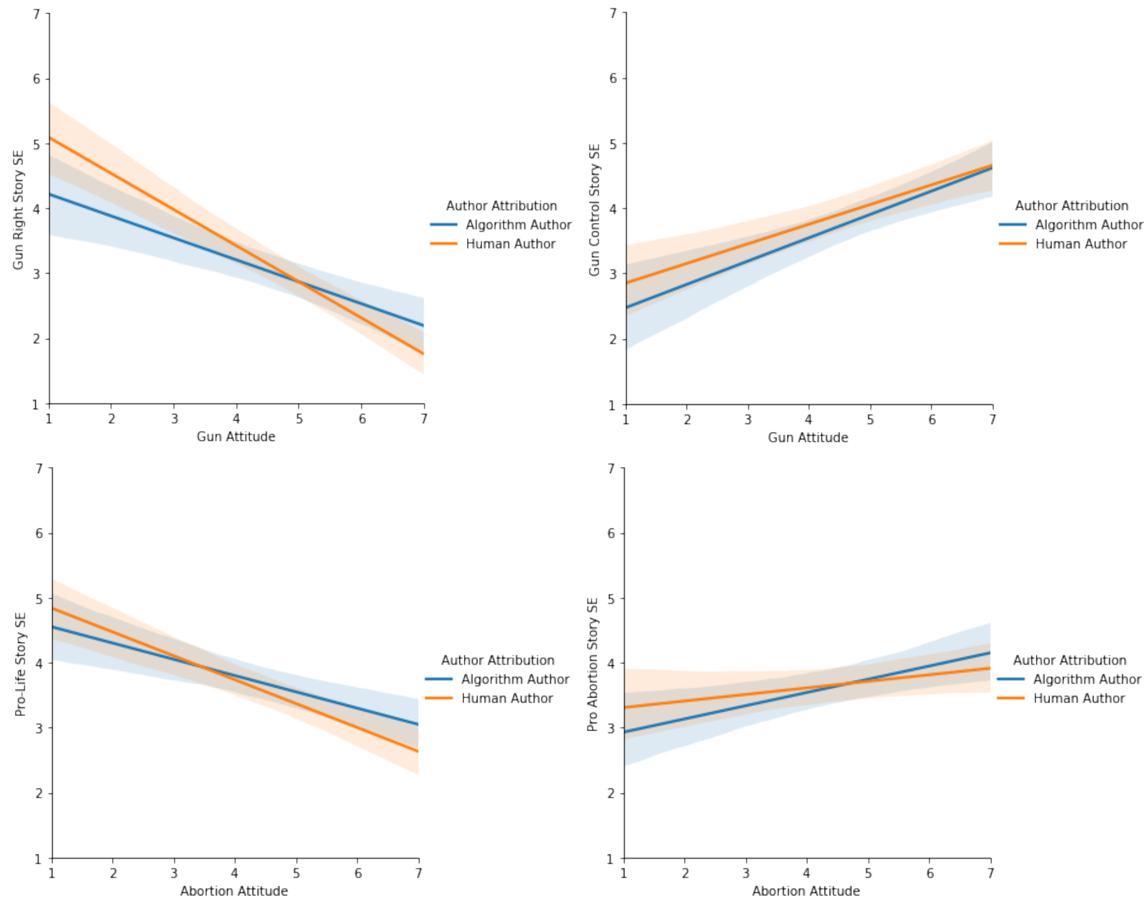

Figure 1. Selective exposure trending lines.

H2 predicted that readers would be more likely to select attitude-consistent human attribution news rather than attitude-consistent algorithmic attribution stories. Significant difference only existed in gun-rights-stories where people were more likely to select attitude-consistent human attribution news (M = 2.99, SD = .13) than attitude-consistent algorithmic attribution stories (M = 2.93, SD = .14), $F(1, 350) = 4.74$, $p < .05$, Wilks' Λ = .99, η^2 = .04. For pro-gun-control stories, people were more likely to select attitude-consistent human attribution news (M = 3.99, SD = .13) than attitude-consistent algorithmic attribution stories (M = 3.82, SD = .14), but the difference was not significant, $F(1, 350) = .74$, $p = .39$, Wilks' Λ = .99, η^2 = .02. For pro-life stories, people were more likely to select attitude-consistent human attribution news (M = 3.66, SD = .13) than attitude-consistent algorithmic ones (M = 3.53, SD = .12), but the difference was not significant, $F(1, 350) = .91$, $p = .34$, Wilks' Λ = 1.00, η^2 = .002. For pro-choice stories, attitude-consistent human attribution news (M = 3.67, SD = .13) and attitude-consistent algorithmic attribution stories (M = 3.65, SD = .14) were not statistically different, $F(1, 350) = 1.07$, $p = .30$, Wilks' Λ = 1.00, η^2 = .002. Although for each topic, people were more likely to select attitude-consistent human attribution news than attitude-consistent algorithmic attribution stories, but significant differences only existed in gun-rights stories. Therefore, H2 was partially supported. The interaction between author attribution and political issue attitude was only significant during the selective exposure process in the gun-rights story, $F(1, 350) = 4.71$, $p < .05$.

H3 predicted that readers would rate attitude-consistent news stories as more credible than attitude-challenging or balanced news for stories purportedly written by both algorithms and humans. Results showed that for the gun topic, there was a statistically significant difference in credibility for both the pro-gun-right story, $F(1, 350) = 87.01$, $p < .001$, and pro-gun-control story, $F(1, 350) = 93.50$, $p < .001$, based on the participant's original gun-issue attitude, Wilks' $\Lambda = .62$, $\eta^2 = .39$. For both human and algorithmic attribution stories, directions were as expected. For the abortion topic, there was a statistically significant difference in credibility for the pro-life story, $F(1, 350) = 9.19$, $p < .01$, and the pro-choice story, $F(1, 350) = 44.90$, $p < .001$, based on participants' original gun issue attitude, Wilks' $\Lambda = .79$, $\eta^2 = .22$. For both human and algorithmic attribution stories, directions were as expected. H3 was fully supported.

H4 predicted that readers would perceive human sources as more credible than algorithm sources. A paired-samples *t* test was used to examine whether significant differences existed in source credibility between algorithm authors and human authors. A *t* test showed people perceived the human source ($M = 4.80$, $SD = 1.02$) as more credible than the algorithmic source ($M = 3.72$, $SD = 1.26$), $t(350) = -13.513$, $p < .001$. H4 was supported.

H5 predicted that readers would perceive human attribution news as more credible than algorithmic attribution stories. A MANOVA was used to test H5. Significant difference only existed in the gun-control story where people perceived algorithmic attribution stories ($M = 4.92$, $SD = .76$) as less credible than human attribution stories ($M = 5.14$, $SD = .71$), $F(1, 350) = 4.49$, $p < .05$, Wilks' $\Lambda = .99$, $\eta^2 = .01$. Although, for each topic, people perceived algorithmic attribution stories as less credible than human attribution stories, significant differences only existed in the gun-control story. Moreover, no significant difference existed between the credibility of human attribution story and algorithmic attribution story in two neutral stories. Therefore, H5 was partially supported, as shown in Table 2.

Table 2. Means Differences of Message Credibility.

		Mean (*SD*)		
Story type		Human author	Algorithmic author	*F*
Gun Story	Gun control	5.14 (.71)	4.92 (.76)	4.49*
	Gun neutral	5.14 (.07)	5.12 (.08)	.26
	Gun rights	3.82 (.09)	3.77 (.10)	.61
Abortion	Pro-life	4.79 (.08)	4.77 (.09)	.56
	Abortion neutral	4.96 (.08)	4.93 (.08)	.17
	Pro-choice	5.00 (.08)	4.90 (.08)	1.55

Note. Row means with common subscripts do not differ significantly from one another. *$p < .05$.

H6 predicted that source credibility would mediate the influence of issue partisanship on selective exposure. A series of mediation models were run by using the PROCESS macro (Hayes, 2013) based on bootstrapping with 1,000 simulations and 95% confidence intervals (CIs). For gun stories, the effect of gun attitudes on selective exposure was partially mediated via source credibility. Indirect, direct, and total effects were all significant because none of these effects include zero for 95% CIs. For gun-rights stories, the indirect effect was a_1b_1 = .03, CI [.01, .06]. The direct effect was c_1 = − .38, CI [−.47, −.30]. The total effect was −.35, CI [−.19, −.03]. For the gun-control story, the indirect effect was a_2b_2 = .05, CI [.02, .08]. The direct effect was c_2 = .25, CI = [.16, .34]. The total effect was .30, CI [.22, .39]. For abortion stories, the mediation effect did not occur. For pro-life stories, the indirect effect was a_1b_1 = .007, CI [−.002, .02]. The direct effect was c_1 = −.303, CI [−.38, −.23]. The total effect was −.296, CI [−.37, −.22]. For pro-choice stories, the indirect effect was a_1b_1 = .02, CI [−.004, .04]. The direct effect was c_1 = .12, CI [.03, .20]. The total effect was .14, CI [.05, .22]. Therefore, H6 was partially supported. Source credibility partially mediated the selective exposure process for gun stories, but not for abortion stories, as shown in Figures 2 and 3.

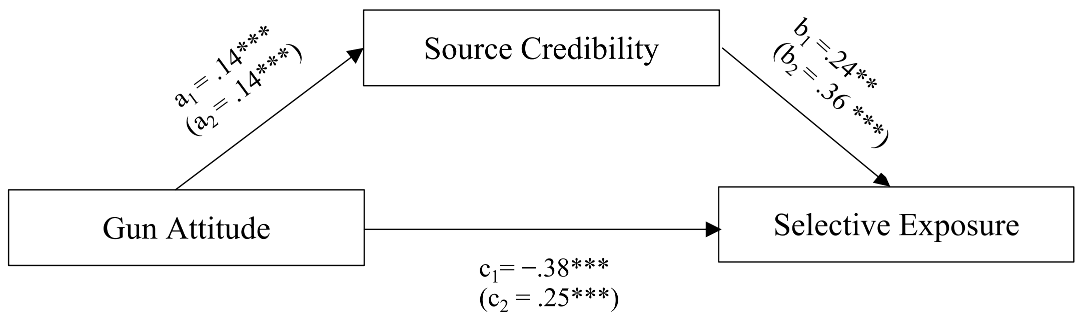

Figure 2. Mediation analysis of pro-gun right (pro-gun control) stories. *p < .05. **p < .01. ***p < .001.

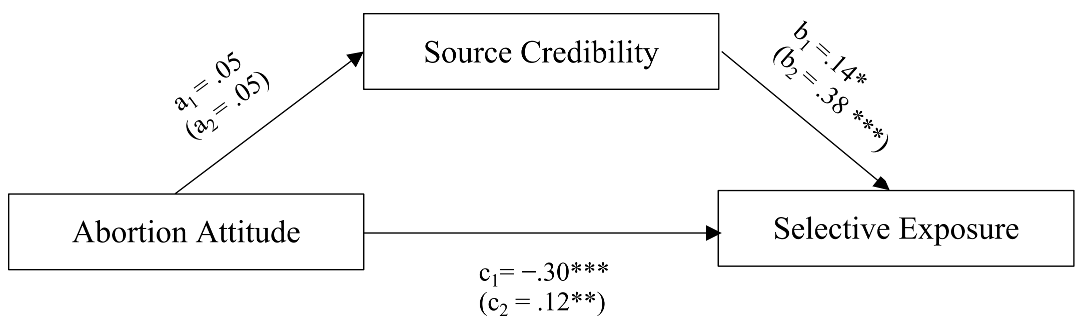

Figure 3. Mediation analysis of pro-life (pro-abortion) stories.

Discussion

Theoretical Implications

With the advent of the Internet and social media, there has been a revival of interest in selective exposure research. Scholars have largely abandoned the cognitive dissonance explanation for selective exposure and suggested a new explanation that is based on credibility perceptions (Metzger et al., 2015). Previous studies revealed selective exposure was linked to source and message credibility, as partisans often selectively expose themselves to information that confirmed their views, and they judged such information as highly credible (Johnson & Kaye, 2013; Westerwick et al., 2017). Automated journalism has become a trending topic in the contemporary media sphere. This study added a new dimension to selective exposure theory by examining the algorithmic and human source attribution in the era of automated journalism. While earlier studies examine whether selective exposure occurs on different platforms and topics, this study examined whether algorithmic author attribution will inspire selective exposure or not.

This study provides several theoretical implications for both automated journalism and selective exposure theory. First, this study found that selective exposure and selective avoidance also occur when people read news attributed to an automated author. Previous studies have shown that people can readily find like-minded news by filtering out news they are not interested in or that is not consistent with their political beliefs (N. Stroud, 2011). In recent years, scholars have contended that the emergence of AI news products (e.g., news recommendation algorithms) increasingly expose readers to more personalized content and thus minimize diverse exposure (also known as filter bubbles; Bakshy et al., 2015; Pariser, 2011). In the domain of automated news, algorithms can be trained to tell personalized stories in multiple languages and from different angles (Jung et al., 2017), which provides a potential opportunity for readers to access more like-minded messages. The importance of the present study is the examination of how the algorithmic authorship influences partisans' perceptions of algorithm-driven content.

Results of this study reveal that people are more likely to choose stories that confirm their opinions and avoid those that challenged their opinions, even if the story is attributed to algorithmic authors. One important finding of this study is that for attitude-consistent gun-rights stories, people are more likely to select human attribution news than algorithmic attribution stories. Further analysis on the mediating role of source credibility suggests that people tend to expose themselves to ideologically consistent news attributed to human sources rather than algorithmic sources because they perceive human sources as more credible. However, it is worth noting that such mediation effects only exist in gun stories, but not in abortion stories. This result can possibly be explained by the nature of two topics. The gun issue has very high relevance to public security (Stoycheff, Pingree, Peifer, & Sui, 2018), whereas abortion stories are more related to personal choices. Therefore, it is not surprising to see that source credibility plays a more significant role in gun stories instead of abortion stories because people may value source credibility more when judging the gun control issue. Another possible explanation for why algorithmic author reduces the selective exposure effect in gun-rights stories is that people may perceive stories with machine heuristics as less politically biased as previous work suggests (e.g., Wang, 2021). Such positive stereotypes about machine neutrality may mitigate partisans' selectivity behaviors.

As Waddell (2019) pointed out, whether audiences should be informed of the contribution of algorithms to the news story is still debatable because the psychological effects of perceived machine authorship remain unknown. Thus, the second prominent contribution of this study is that it further studies whether the difference of credibility between human source and algorithms source affects people's perceptions of attitude-consistent information. Results show that news attributed to humans is rated as more credible than news attributed to algorithms, which is consistent with previous studies (Waddell, 2019). Both Waddell's (2019) work and this study use professional reporters to describe the human source of stimuli, which may increase the perceived credibility of human sources as individuals tend to perceive journalists as credible and professional.

The third main theoretical contribution of the present study is that it provides strong evidence that the credibility explanation stays true in the realm of machine attribution stories. Scholars have different explanations about what makes selective exposure occur, among which, the credibility explanation for selective exposure suggests information that is congenial with an individual political predisposition is perceived as higher quality and therefore more credible than contradictory information (Fischer et al., 2005; Melican & Dixon, 2008). The present work found for both human and algorithm authorship attribution news, attitude-consistent news is rated as more credible than attitude-challenging news. These results not only provide supplemental evidence for previous selective exposure work that people perceive congenial information as more credible than challenging information but also shed light on how source credibility affects people's selectivity behaviors.

Limitations and Future Research

Despite these contributions to the automated journalism and selective exposure studies, this work had certain limitations. First, this study used MTurk to recruit participants. Even though past work shows that many scholars in social sciences use MTurk to conduct experimental studies (M. D. Buhrmester, Talaifar, & Gosling, 2018; Mullinix, Leeper, Druckman, & Freese, 2015), the reliability of MTurk samples needs to be further tested (Y. Wu, 2020). MTurk samples cannot fully represent the overall population, especially in terms of political ideology, because respondents self-select studies to participate in. Future research should endeavor to find more representative samples in terms of political issue attitudes. Also, the sample for this study was limited to the United States. Previous studies suggest the United States serves as an outlier with high levels of both political polarization and selective exposure, so results from this study may not be generalized to other nations. Future studies should explore the source effects of human versus automated source attribution among various countries with different media and political systems.

Second, the current measurement of selective exposure has limitations. Earlier studies asked about the likelihood of people connecting to online sources that share their point of view (e.g., Johnson & Kaye, 2013) or select the same website again in the future (Metzger et al., 2015). This current study intentionally changed the wording from "connect to the source/website" to "connect to this article" because there may be a confounding effect that many participants choose not to connect to the algorithmic source again because they rarely encounter automated news in the real world. Admittedly, this measure is imperfect, because people may not return to the same article, as they already read it before. Future studies can create better measures of selective exposure to algorithmic sources based on the current pioneering study.

Third, in terms of source credibility, the reputation of automated news generated by different algorithm providers has not been extensively examined. For instance, this study did not examine whether a piece of news attributed to an algorithm provider with a strong reputation would differ from news presented by a small unknown company in terms of selective exposure. This study only examined reporters as human sources. Future work can study other human sources, such as family and friends, politicians, and issue experts. Future studies can investigate how the reputation heuristic will affect selective exposure by examining different algorithm providers and human sources. Besides, the present study used the same interface, a fake news website screenshot, for both algorithm and human author attribution news to test whether selective exposure existed. Future studies can include more actual media channels, such as news websites or social media platforms, to examine how algorithm authors on different message channels will affect people's selectivity.

Conclusion

As a new technological affordance, automated journalism not only speeds up the news production process but also alters readers' perceptions of news. Some scholars hope algorithms can be a solution to reduce polarization because algorithms are regarded as unbiased and neutral. This study suggests that selective exposure still occurs when people read news attributed to an automated author on politically charged topics. Even so, algorithmic author attribution may reduce the selective exposure effect compared to human author attribution in gun-rights stories. This study added a new dimension to the selective exposure theory by detecting that people are inclined to select attitude-consistent news no matter whether the author attribution is an algorithm or human. This work also laid a foundation for future studies to examine how algorithmic and human author attribution and source credibility will affect people's selectivity.

In addition to the theoretical contribution to selective exposure theory and credibility, this study has important practical implications for the news industry. Good news for newsrooms is that this study found no significant difference between the credibility of news attributed to humans and news attributed to algorithms among neutral stories. Previous studies show news organizations often avoided disclosing algorithmic sources (Montal & Reich, 2017; Tandoc et al., 2020). However, this study provides optimistic results, which suggest that newsrooms can disclose algorithmic sources for neutral news stories without worrying that credibility of algorithms would affect people's perceptions and selectivity behaviors.

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