Belief in or Identification of False News According to the Elaboration Likelihood Model

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Based on the elaboration likelihood model, this study examines the influence of central and peripheral cues on a user's belief in or identification of false news and investigates the direct and moderating effects of information literacy. The results indicated that argument quality enables social media (SM) and news website (NW) users to identify false messages. Topical relevance contributed to a user's belief in false news (BFN) in the SM group but had no impact in the NW group. Image appeal had no impact in either group. Source credibility was associated with BFN in the SM group. Additionally, source credibility and homophily contributed to the identification of false messages in the NW group. Information literacy enabled individuals to identify false information only in the NW group, but it had no moderating effect on the relationship between informational cues and BFN.

Keywords: false information, fake news, elaboration likelihood model, information literacy

Although fake or false news has existed since the earliest writing systems (Marcus, 1993), the term "fake news" has recently become prominent due to its global implications and worldwide concern. Negative consequences of online fake news have been observed at individual and societal levels and have included fluctuations of stock prices (Rapoza, 2017), health crises during the Ebola outbreak (Oyeyemi, Gabarron, & Wynn, 2014), and the political fallout of the 2016 U.S. presidential election (Allcott & Gentzkow, 2017). To combat the damage caused by false stories, considerable public discourse on solutions has arisen—such as, detection by AI technology, fact-checking by human effort, and empowering the public by information

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Date submitted: 2020–03–06

[1] This work is supported by grants from the Ministry of Science and Technology in Taiwan (Grant No. 108-2634-F-468-001).

literacy education. However, the core issue is probably being able to determine what factors contribute to people's susceptibility to believing false content in an online context. This topic remains unexplored and is what this study investigates.

Because social media (SM) has been criticized as a potentially fertile ground for the dissemination of fakes, congressional committees have asked executives from Facebook, Google, and Twitter to confirm their efforts to combat false stories (Popken, 2018; Shaban, Timberg, & Dwoskin, 2017). Mark Zuckerberg, the CEO of Facebook, told Congress that Facebook would use AI to detect fakes. In addition to extracting content features from text and images, AI systems can evaluate the likelihood of a story being false by identifying social context features, including the features of users, generated posts, and networks (Shu, Sliva, Wang, Tang, & Liu, 2017). However, the creators of false content often change their methods to improve the apparent authenticity of the content and circumvent detection. Adopting such strategies leads to an ongoing competition with fake-news detection technologies. The use of AI to combat false news has been criticized as instigating a technological arms race (Cole, 2018; Susarla, 2018).

Besides, fact-checking organizations have been established in many countries as concerns regarding the damage caused by fake information increase. According to the Duke Reporters' Lab, by April 2020, 237 fact-checking organizations were operating worldwide. Fact-checking is a process through which the veracity of data or documents is investigated and established; thus, it is intellectually demanding, time-consuming, and heavily dependent on human effort, and its efficiency and scalability are limited. In addition, online fake news has been found to disseminate considerably faster and more broadly compared with that of traditional media (Vosoughi, Roy, & Aral, 2018); by 2022, people in developed economies may encounter more false than real news (Susarla, 2018). Despite their efforts, fact-checkers would be unable to meet demand, and much (perhaps most) false information would remain undetected. An undetected false story may be believable due to the "implied truth effect"—that is, the absence of a warning may be perceived as a verification of the story (Pennycook, Bear, Collins, & Rand, 2020).

AI algorithms and fact-checking are both unsatisfactory methods to combat fake news. Therefore, because humans are more likely than robots to spread false information, individuals should be emphasized when addressing the threat of false news (Khan & Idris, 2019; Vosoughi et al., 2018). A large-scale cascade of false information can become viral within minutes through individuals sharing and retweeting. Moreover, people often spread information without verification (Zubiaga & Ji, 2013) or share news without reading the whole article (Gabielkov, Ramachandran, Chaintreau, & Legout, 2016). Individuals with high information literacy are less likely to be misled because they are accustomed to critical thinking and distinguishing false and accurate information (Fallis & Whitcomb, 2009). Thus, improving information literacy is suggested as a strategy to combat the rising challenge of fake news.

Despite considerable discourse on combating the dissemination of false stories, the causes of susceptibility to believing false news in an online context remain unexplored, and the potential for information literacy to mitigate this vulnerability is unclear. Some studies have investigated the relationship between audience characteristics and the extent to which individuals believe false news, with results indicating that the absence of analytical thinking and an active, open mind was associated with increased belief in false information (Bronstein, Pennycook, Bear, Rand, & Cannon, 2019). In addition, repeated exposure to false stories increased their perceived accuracy (Pennycook, Cannon, & Rand, 2018). Moreover, sensational or novel content in false stories led these stories to be spread faster than real news (Vosoughi et al., 2018). Online platforms, especially SM, are perceived as facilitators for the distribution of false news because they embrace the bandwagon heuristic (Thorson, 2008) and blur the information source through likes or shares (Kang, Bae, Zhang, & Sundar, 2011); thus, the online context plays a substantial role in the promotion of belief in false news. However, few studies have investigated this role. To fill this knowledge gap, the current study explores the impacts of online factors that are associated with belief in or identification of false information, as well as the direct effect and moderating role of information literacy.

The elaboration likelihood model (ELM), developed by Petty and Cacioppo (1984), is a dual-process theory of attitude formation and change resulting in persuasion outcomes. This model has often been employed in information technology persuasion research, such as consumer responses to online advertising (Cyr, Head, Lim, & Stibe, 2018). The model claims that persuasion is incurred through a central route, such as the strength of the arguments presented in a message or through a peripheral route, such as the attractiveness of the message source, image appeal, and homophily. These routes are analogous to news content and social context in the AI detection methodology for fake news. Therefore, this study was based on the ELM model, and the result is expected to reveal the impact of online factors on susceptibility to believing false news as well as to offer insights into AI detection. Specifically, this study answers two research questions: (1) In an online context, what factors increase the identification of false information and susceptibility to believing false stories? (2) Does information literacy play a moderating role that can mitigate this vulnerability?

Theoretical Background and Literature Review

The Science of Fake News

Following the concern that Russia might meddle with the 2016 U.S. presidential election, "fake news" has become an increasingly widely used term. In addition to academic discourse, this term has recently entered the mainstream vernacular and has been used to indicate false stories, stigmatize information presented from opposing viewpoints, and even discredit critical reports by news organizations (Tandoc, Lim, & Ling, 2018). Because the term "fake news" has different meanings in different contexts and might thus be misleading, the UK government decided to ban this term in policy documents and official reports (Murphy, 2018).

Much of pre-2016 discourse on fake news conflates the notions of misinformation and disinformation (Wardle, 2017). Misinformation refers to "misleading information created or disseminated without manipulative or malicious intent," and disinformation refers to "deliberate (often orchestrated) attempts to confuse or manipulate people through delivering dishonest information to them" (UNESCO, 2018, p. 7). Previous categorizations of fake news have been broader and have focused on either the authenticity or intent of information (Shu et al., 2017). Following the aftermath of the 2016 U.S. presidential election, the definition of fake news has highlighted both authenticity and intent. For example, fake news was defined as "news articles that are intentionally and verifiably false, and could mislead readers" (Allcott & Gentzkow, 2017, p. 213) or as "information deliberately fabricated and published with the intention to deceive and mislead others into believing falsehoods or doubting verifiable facts" (McGonagle, 2017, p. 203). Moreover, some studies have identified the main intentions of fake news creation as economic and ideological, such as attracting clicks and converting audience size into marketing profits, demeaning certain actors or states, instigating emotions, and influencing elections for political advantage (Allcott & Gentzkow, 2017; Kirby, 2016; Lazer et al., 2018).

Various political studies have used the term "fake" to refer to related but distinct types of content, such as news parodies, political satires, and propaganda. News parodies and satire contain irony and exaggeration, but the humor is transparent. However, satire is based on actual events, whereas news parody plays on the absurdity of current affairs by describing fictitious news stories. In addition, propaganda is often based on facts, but enhances a perspective for the primary intention of misleading audiences (Tandoc et al., 2018; Zannettou, Sirivianos, Blackburn, & Kourtellis, 2019). Figure 1 illustrates the broad typology of fake information with a point indicating the current definition of fake news, which highlights fabrication and misleading intention. Notably, authenticity refers to verifiable facts or events that are not applicable to subjective reports or commentary.

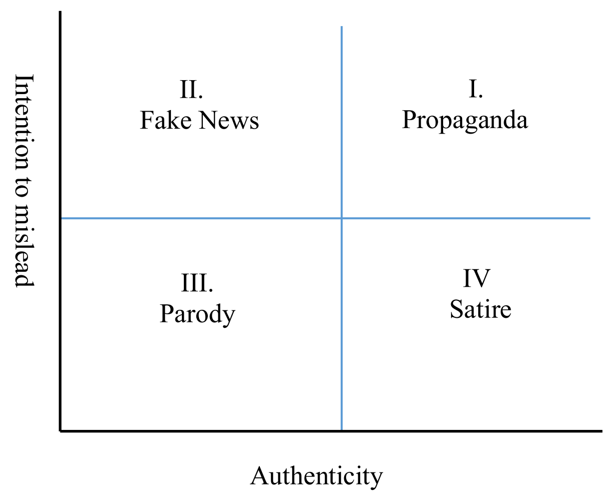

Figure 1. Fake information typology.

With the growing concern about false news, numerous studies have attempted to explore its distribution and effects; however, studies should be cautious in using the term "fake." Because fake news is created based on a malicious motivation, it may be difficult to distinguish it from other false information through content and linguistic analysis alone (Shu et al., 2017). Many fact-checking organizations avoid using the term "fake." For example, PolitiFact uses a Truth-O-Meter with six ratings—namely, true, mostly true, half true, mostly false, false, and pants on fire. This study employs the term "false," which refers to verifiable inaccuracies in content, because news stimuli in the study were verified as false by the Taiwan FactCheck Center.

False information can cause serious damage when spread widely during a short period. Although SM bots have been blamed for the rapid dissemination of false information, studies have found that individuals are responsible for spreading inaccurate or false stories through intentional or unintentional information-sharing behavior (Wu, Morstatter, Hu, & Liu, 2016). Moreover, false stories are spread faster than real news (Vosoughi et al., 2018). According to Shi, Hu, Lai, and Chen (2018), a user's sharing behavior is associated with the information quality and source credibility. Therefore, we propose the following hypothesis:

H1: Belief in false news (BFN) is associated with sharing intent (SI).

Elaboration Likelihood Model (ELM)

As briefly outlined in the introduction, the ELM was developed to investigate social psychology and suggests a dual-route process of attitude formation and persuasion outcomes. The ELM has been applied to examine user attitude and subsequent behavior or intent in several information systems studies, particularly for exploring the influencing process of persuasive online communication. For example, Bhattacherjee and Sanford (2006) examined information technology (IT) acceptance and identified the influence process in IT acceptance. Lee, Park, and Han (2008) and Kang and Namkung (2019) have investigated the online cues that influence consumer attitude and decision making toward a product. Kim, Chung, Lee, and Preis (2016), Meng and Choi (2019), and Wang (2015) have investigated the process of persuasive online communication with tourists. In addition, Cyr and associates (2018) explored the effects of argument quality as a central route versus design and social elements as peripheral routes on the influence of attitude change on a specific controversial topic. The ELM has been thoroughly documented in varied fields. Thus, because believing false contents is also a process of persuasion, this study applies the ELM to investigate the persuasive processes involved in false information.

The ELM indicates that an individual's persuasion process differs according to the extent to which they elaborate on the topic. When a topic is relevant to an individual, they may take the time to read and process the arguments presented; thus, they engage in central route processing. By contrast, if a topic is less relevant, individuals who lack the motivation exert less effort and tend to rely on easily processed peripheral cues in the communication (Bhattacherjee & Sanford, 2006). Therefore, the mechanism in the central route is message related and argument oriented, whereas the peripheral route is cue oriented. Many studies have found that argument quality and topical relevance are essential in the central route. For example, Angst and Agarwal (2009) explored the persuasion process in the adoption of electronic health records. Their results indicated that higher argument quality and topic involvement effected attitudes and increased willingness to use electronic health records. Studies in the context of online tourism have revealed significant effects of argument quality on consumer attitude change and use intent (Kim et al., 2016; Meng & Choi, 2019; Wang, 2015). Because of these findings, this study proposes the following hypotheses:

H2: Argument quality influences BFN.

H3: Topical relevance is associated with BFN.

When processing messages cognitively in the central route, individuals in high elaboration likelihood states are persuaded by argument quality or the inclusion of relevant information. By contrast, those in low elaboration likelihood states are inclined to be motivated by peripheral cues such as images, sources, and social networks. Images, for example, can have a substantial impact on receivers. According to Chen and

Chang (2019), images are used by female politicians to change public perceptions of stereotypically female traits that are most closely related with incompetence on tough issues. Moreover, among a candidate's Facebook posts, those receiving many likes and shares are often messages with sensational pictures, such as the candidate speaking confidently to a varied crowd of supporters at a campaign rally. Similarly, studies have indicated that, as an advertising trigger, image content yields more emotional processing than does text, thus influencing consumers' attitudes toward a product or service (Lee, Amir, & Ariely, 2009; Poor, Duhachek, & Krishnan, 2013). When exposed to an advertisement with both image and text, consumers are likely to notice the image first because images are processed more quickly and spontaneously than are texts because of the direct connection between an image and its meaning. Numerous studies have confirmed that images play an important role in advertising and have a significant impact on customer attitudes and behavioral outcomes (Jaeger & MacFie, 2001; Luna & Peracchio, 2003; Townsend & Kahn, 2014; Xu & Huang, 2019). Cyr and colleagues (2018) examined individual persuasion in the Keystone pipeline case based on the ELM model. In their study, the stimuli were a picture of a rally showing people with placards supporting the project and some images of maps depicting the refinery and the pipeline route. Their results confirmed the hypothesis that if individuals find the images on the website useful and convincing, they will be encouraged to support the project. Hence, this study proposes the following hypothesis:

H4: Image appeal has an impact on BFN.

Source credibility indicates whether a message receiver trusts the sender. It is an important factor in decision making, particularly in the ambiguous online context (Mak, Schmitt, & Lyytinen, 1997). As a peripheral cue, source credibility is likely to affect attitude change because peripheral cues appeal to human affect instead of rational judgment. For example, celebrity endorsements are a peripheral cue that enhance source credibility by influencing users' human affect (Bhattacherjee & Sanford, 2006). In an online environment, source credibility positively influences the perceived usefulness of the information. If consumers believe that comments are posted by individuals with a high credibility, they have a higher perception of the usefulness of the comments, which subsequently yields changes in attitude or behavior (Cheung, Lee, & Rabjohn, 2008; Kang & Namkung, 2019; Kim et al., 2016). Under high ambiguity or with unclear evidence, source credibility can influence persuasion because heuristic processing can bias cognitive processing (Chaiken & Maheswaran, 1994). Based on these findings, this study proposes the following hypothesis:

H5: Source credibility is related to BFN.

In addition to source credibility, the relationship between the source and receiver also plays a role in the receiver's decision-making process. When a source is perceived as homophilic to the users, it means that the users have similarities in attitudes, tastes, and beliefs; these internal states are presumed to determine an individual's orientation toward future behavior (Lazarsfeld & Merton, 1954). Contact occurs at a higher rate among similar people than among dissimilar people; thus, homophily leads to attraction and interaction (McPherson, Smith-Lovin, & Cook, 2001). Homophilic sources are preferred as information sources and are more influential because similarity of tastes between the source and user is likely to invoke interest (De Bruyn & Lilien, 2008; Shi et al., 2018; Steffes & Burgee, 2009). Thus, we propose the following hypothesis:

H6: Homophily influences BFN.

Information Literacy

As discussed above, Internet users may play a central role in combating false information because relying on AI to identify false information could lead to a technological arms race. Bode and Vraga (2018) conducted an experimental study and proved that users can reduce or mitigate the effects of health misinformation if they can critically assess it and attempt to verify its veracity by searching for evidence. With the dissemination of increasingly sophisticated false information, individuals in today's media environment must be information literate (Hargittai, 2010; Khan, Wohn, & Ellison, 2014; Van Deursen & van Dijk, 2009). Initial concepts of digital or information literacy reflected of the simpler nature of the Internet at that time, such as the ability to browse Internet sites and download files. The introduction of SM platforms as vital sources of news and information has shifted the focus of information literacy toward evaluating the integrity of online information and differentiating false stories from true information (Khan & Idris, 2019). Therefore, by information literacy, we refer to the abilities of information searching, sharing, and verification. Thus, this study proposes the following hypotheses:

H7: *Information literacy has an impact on BFN.*

H8: *Information literacy has a moderating effect on the relationships of argument quality (H8a), topical relevance (H8b), image appeal (H8c), source credibility (H8d), and homophily (H8e) with BFN.*

Based on this discussion, we propose a dual-route research model, as illustrated in Figure 2.

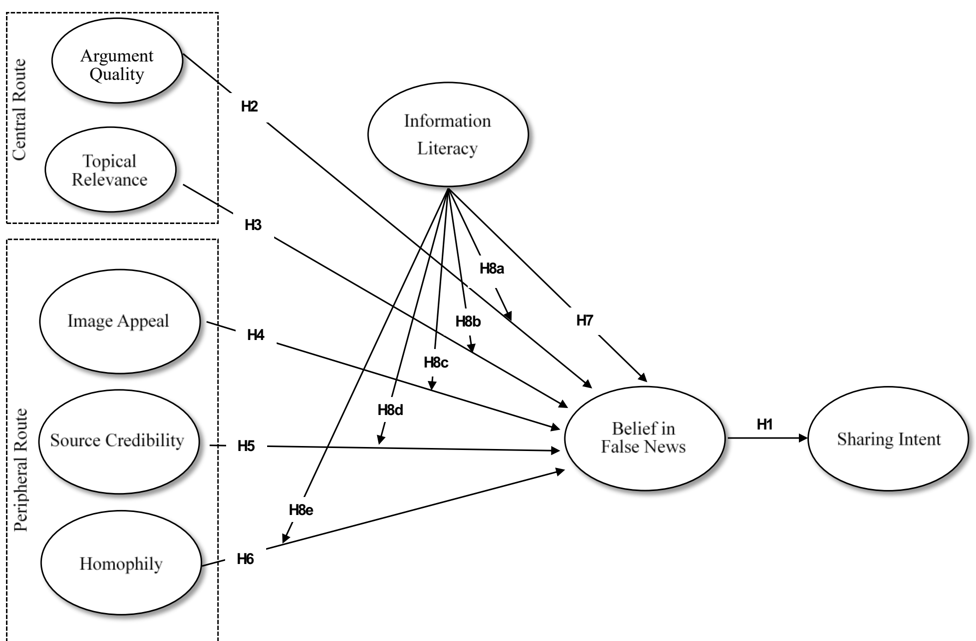

Figure 2. Research model.

Method

Participants and Procedure

Participants were students from Asia University, Taiwan, ages approximately 20 years, and students from Taichung community colleges, ages older than 30 years. We used a convenience sampling method to randomly select classes offered by the College of Information and Electronic Engineering at Asia University and Taichung Community College. Participants encountered false news in an online context and then completed an online measurement. We reviewed more than 100 fact-checking reports from Taiwan FactCheck Center and selected four news judged false—two from SM (Facebook and LINE) and two from news websites (NWs). Participants were presented with one of the four false news items and were then asked to complete an online survey. In Study A, 227 participants were shown a policy-related news article from Facebook; in Study B, 236 participants were presented with false news concerning a vision test obtained from LINE; in Study C, 221 participants were asked to read a policy-related message from a NW; and in Study D, 247 participants were presented with a news item about house cleaning obtained from another NW. Data from Studies A and B were combined to analyze the model structure for believing in false information obtained through SM, and data from Studies C and D were combined to analyze the model structure for believing in false information obtained through NWs. Because social media platforms have been specifically blamed for the dissemination of false news, we compared the predictive factors for belief in or identification of false messages in the SM group and the NW group. Table 1 presents the demographic data.

Table 1. Sample Demographics.

	Total	Male	Female	Age (*M*, *SD*, Min~Max)
SM group	463	197 (42.5%)	266 (57.4%)	39.53, 17.97, 18~70
Study A	227	90 (39.6%)	137 (60.4%)	38.99, 18.04, 18~70
Study B	236	107 (45.3%)	129 (54.7%)	40.06, 17.92, 18~70
NW group	468	218 (46.5%)	250 (53.4%)	36.69, 16.96, 18~73
Study C	221	111 (50.2%)	110 (49.8%)	36.95, 16.24, 18~73
Study D	247	107 (43.3%)	140 (56.7%)	36.48, 17.62, 18~70

Measurement

In this study, an online survey was developed to measure central cues (argument quality and topical relevance), peripheral cues (image appeal, source credibility, and homophily), information literacy, BFN, and SI. To measure their BFN, participants were asked to rate the accuracy of the presented information on a 5-point scale ranging from 1 (*not at all accurate*) to 5 (*very accurate*). To measure their SI, the participants were asked to rate their intention to share the presented information by using a 5-point Likert scale ranging from 1 (*highly disagree*) to 5 (*highly agree*).

The six constructs in this study (argument quality, topical relevance, image appeal, source credibility, homophily, and information literacy) were measured using multiple-item perceptual scales based on prevalidated items from previous studies that were reworded for consistency with the current research context. The four items used to measure argument quality were adapted from research by Kim and associates (2016) and Wang (2015). To measure topical relevance, we adapted two items from the study by Shi and colleagues (2018). The four items used to measure image appeal were obtained from the study by Cyr and associates (2018). Source credibility was measured using two items adapted from previous studies by Bhattacherjee and Sanford (2006), Kang and Namkung (2019), and Kim and colleagues (2016). To measure homophily, we adapted two items from studies by Shi and associates (2018) and Steffes and Burgee (2009). Three items from studies by Bode and Vraga (2018) and Khan and Idris (2019) were adopted to measure information literacy. All the items were assessed using the same 5-point Likert scale ranging from 1 (*highly disagree*) to 5 (*highly agree*).

In total, 19 questionnaire items were prepared (see the Appendix). However, one item for source credibility was omitted after data collection because it did not meet the criteria for confirmatory factor analysis (see the Content and Construct Validity section). Therefore, the analysis was based on survey data for the remaining 18 items.

Analysis

Structural equation modeling (SEM) was conducted to test the hypotheses by using SmartPLS. The partial least squares (PLS) path modeling method is appropriate for testing models in the early stage of development (Urbach & Ahlemann, 2010). In the absence of ELM-based research into users' information processing model for false messages or the interaction effect of information literacy, we consider PLS to be a suitable analysis method. A positive association value between a central or peripheral cue and BFN implies that this cue increases susceptibility to believing false news. Alternatively, a negative association indicates that this cue increases the identification of false information.

Results

Content and Construct Validity

In this study, survey items were adapted from previously validated studies; thus, content validity for the survey items was confirmed. To assess the construct validity, a PLS approach to confirmatory factor analysis (CFA) was applied; Tables 2 and 3 provide the cross-loading matrices for the SM and NW groups, respectively. When using the PLS CFA approach to assess discriminant validity, the factorial loading values of measurement items on their respective latent constructs should be greater than their loadings on other constructs (Hair, Hult, Ringle, & Sarstedt, 2017). As shown in Tables 2 and 3, this recommendation for validity testing is satisfied.

Table 2. Cross-Loading Matrix (SM Group).

	BFN	SI	AQ	TR	IA	SC	HM	IL
BFN	1.000	.704	−.334	−.159	−.189	−.289	−.173	−.222
SI	.704	1.000	−.308	−.081	−.158	−.257	−.117	−.179
AQ1	−.326	−.279	.862	.047	.189	.172	−.031	.364
AQ2	−.289	−.265	.836	.058	.213	.200	−.182	.368
AQ3	−.210	−.206	.785	.043	.275	.213	−.142	.326
AQ4	−.256	−.256	.817	.011	.252	.171	−.105	.252
TR1	−.157	−.052	.045	.974	.338	.498	.274	.239
TR2	−.153	−.106	.050	.973	.324	.508	.335	.204
IA1	−.139	−.126	.231	.316	.798	.303	.153	.221
IA2	−.178	−.141	.270	.310	.843	.308	.147	.252
IA3	−.132	−.121	.181	.154	.733	.313	−.102	.304
IA4	−.132	−.101	.157	.268	.737	.375	.037	.285
SC	−.289	−.257	.226	.517	.413	1.000	.151	.228
HM1	−.164	−.115	−.116	.274	.044	.113	.922	−.175
HM2	−.154	−.099	−.129	.300	.115	.165	.911	−.091
IL1	−.146	−.136	.379	.202	.267	.177	−.030	.572
IL2	−.200	−.158	.274	.191	.261	.181	−.097	.888
IL3	−.174	−.130	.317	.154	.277	.184	−.212	.876

BFN = belief in false news; SI = sharing intent; AQ = argument quality; TR = topical relevance; IA = image appeal; SC = source credibility; HM = homophily; IL = information literacy.

Discriminant validity is assessed by examining interconstruct correlations; the correlations between constructs should be lower than the square root of the average variance of items within a construct. Tables 4 and 5 indicate that this criterion is satisfied. In addition, the Cronbach's alpha values are higher than 0.6. The acceptable range for Cronbach's alpha is 0.5 or higher, and ideally, higher than 0.7 (Rivard & Huff, 1988). Similarly, the composite reliability of each construct exceeds the recommended threshold of 0.7, and the average variance extracted (AVE) of each construct exceeds the recommended threshold of 0.5 (Gefen & Straub, 2005). Therefore, the study instrument has satisfactory construct validity.

Table 3. Cross-Loading Matrix (NW Group).

	BFN	SI	AQ	TR	IA	SC	HM	IL
BFN	1.000	.725	−.409	.509	−.204	.375	−.137	−.218
SI	.725	1.000	−.332	.458	−.142	.383	−.178	−.174
AQ1	−.320	−.265	.750	−.393	.364	−.221	.294	.207
AQ2	−.420	−.364	.842	−.517	.291	−.314	.279	.327
AQ3	−.164	−.111	.681	−.186	.315	−.301	.335	.190
AQ4	−.213	−.134	.716	−.293	.288	−.300	.317	.242
TR1	.509	.458	−.508	.817	−.212	.359	−.181	−.257
TR2	.501	.456	−.512	.823	−.213	.352	−.179	−.260
IA1	−.134	−.016	.190	−.052	.670	−.162	.244	.263
IA2	−.196	−.160	.423	−.251	.866	−.116	.317	.270
IA3	−.126	−.125	.223	−.151	.792	.080	.296	.281
IA4	−.231	−.139	−.126	−.216	.798	.083	.153	.221
SC	.375	.383	−.368	.359	−.097	1.000	−.287	−.118
HM1	−.125	−.178	.353	−.174	.341	−.245	.882	.283
HM2	−.112	−.128	.319	−.137	.303	−.253	.849	.123
IL1	−.162	−.156	.096	−.024	.173	.013	.088	.642
IL2	−.201	−.151	.361	−.284	.318	−.172	.227	.892
IL3	−.167	−.117	.336	−.300	.352	−.110	.262	.893

BFN = belief in false news; SI = sharing intent; AQ = argument quality; TR = topical relevance; IA = image appeal; SC = source credibility; HM = homophily; IL = information literacy.

Table 4. Interconstruct Correlation Matrix (SM Group).

	Cronbach's alpha	Composite reliability	AVE	BFN	SI	AQ	TR	IA	SC	HM	IL
BFN	1.000	1.000	1.000	1.000							
SI	1.000	1.000	1.000	.704	1.000						
AQ	.846	.895	.681	−.334	−.308	.825					
TR	.945	.973	.947	−.159	−.081	.049	.973				
IA	.784	.860	.607	−.189	−.158	.274	.340	.779			
SC	1.000	1.000	1.000	−.289	−.257	.226	.517	.413	1.000		
HM	.809	.913	.840	−.173	−.117	−.133	.313	.086	.151	.916	
IL	.681	.830	.628	−.222	−.179	.400	.228	.337	.228	−.147	.792

BFN = belief in false news; SI = sharing intent; AQ = argument quality; TR = topical relevance; IA = image appeal; SC = source credibility; HM = homophily; IL = information literacy.

Table 5. Interconstruct Correlation Matrix (NW Group).

	Cronbach's alpha	Composite reliability	AVE	BFN	SI	AQ	TR	IA	SC	HM	IL
BFN	1.000	1.000	1.000	1.000							
SI	1.000	1.000	1.000	.725	1.000						
AQ	.761	.836	.562	−.409	−.332	.749					
TR	.817	.821	.835	.509	.458	−.508	.822				
IA	.651	.809	.588	−.204	−.142	.410	−.212	.767			
SC	1.000	1.000	1.000	.375	.383	−.368	.359	−.097	1.000		
HM	.666	.857	.749	−.137	−.178	.389	−.181	.373	−.287	.866	
IL	.738	.855	.668	−.218	−.174	.334	−.257	.349	−.118	.240	.817

BFN = belief in false news; SI = sharing intent; AQ = argument quality; TR = topical relevance; IA = image appeal; SC = source credibility; HM = homophily; IL = information literacy.

SM Group Structural Model

Figure 3 depicts the results of model for the SM group (*n* = 463). The R^2 values for BFN and SI are .318 and .525, respectively. BFN was highly associated with SI (H1). Argument quality negatively influenced BFN (H2), whereas topical relevance and source credibility positively influenced BFN (H3 & H5). For image appeal and homophily, the results were not significant (H4 & H6). Information literacy was not related to BFN and did not moderate any of the central and peripheral cues; thus, H7 and H8 are not supported. In conclusion, hypotheses H1, H2, H3, and H5 are supported, whereas H4, H6, H7, and H8 are not supported. Table 6 provides a summary of the hypotheses and the results.

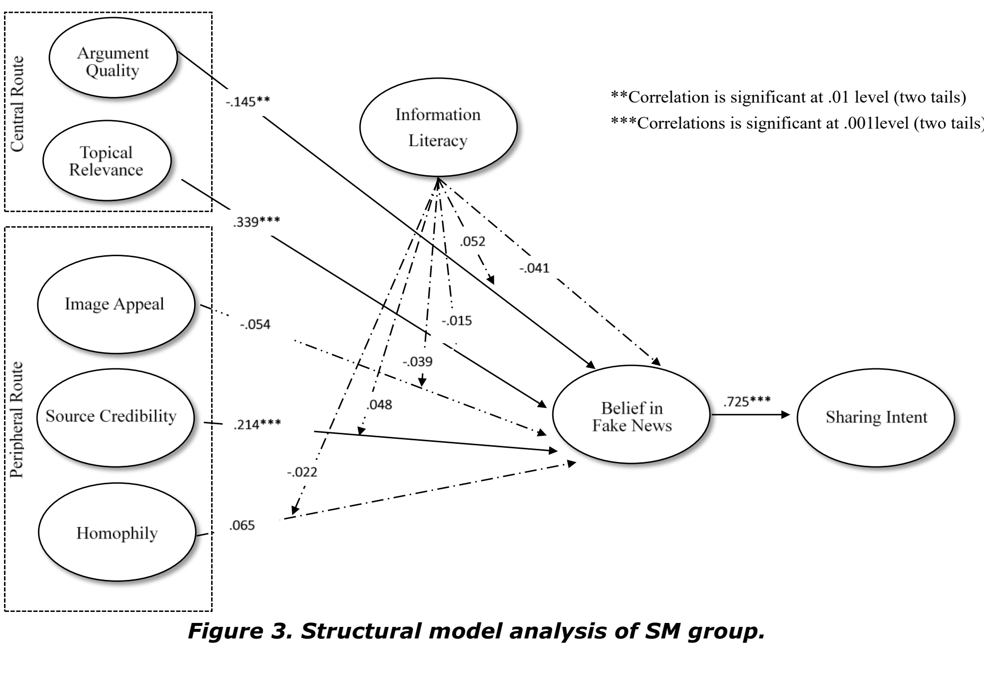

Figure 3. Structural model analysis of SM group.

NW Group Structural Model

Figure 4 depicts the results of the model for the NW group (*n* = 468). The R^2 values for BFN and SI are .192 and .495, respectively. BFN was highly associated with SI (H1). Argument quality, source credibility, and homophily all negatively influenced BFN (H2, H5, & H6). For topical relevance and image appeal, the results were not significant (H3 & H4). Different from the result in the SM group, information literacy was negatively associated with BFN (H7). However, similarly to the SM group, information literacy moderated none of the central and peripheral cues (H8).

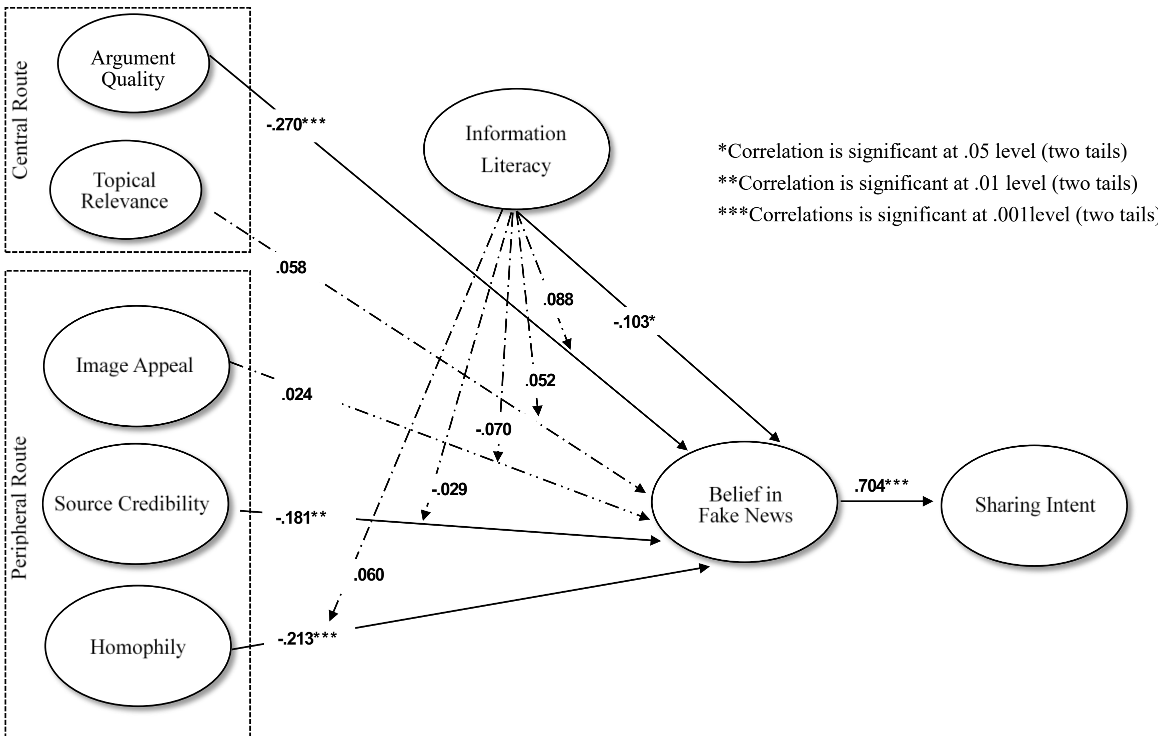

Figure 4. Structural model analysis of NW Group.

In conclusion, hypotheses H1, H2, H5, H6, and H7 are supported, whereas H3, H4, and H8 are not supported. A summary of the hypotheses and the results is shown in Table 6.

Table 6. Hypotheses Results.

Hypothesis	SM Group	NW Group
H1: BFN is associated with sharing intent SI.	Supported ($\beta = .725$, $p < .001$)	Supported ($\beta = .704$, $p < .001$)
H2: AQ influences BFN.	Supported ($\beta = -.145$, $p < .01$)	Supported ($\beta = -.27$, $p < .001$)
H3: TR is associated with BFN.	Supported ($\beta = .339$, $p < .001$)	Not supported
H4: IA has an impact on BFN.	Not supported	Not supported
H5: SC is related to BFN.	Supported ($\beta = .214$, $p < .001$)	Supported ($\beta = -.181$, $p < .01$)
H6: HM influences BFN	Not supported	Supported ($\beta = -.213$, $p < .001$)
H7: IL has an impact on BFN	Not supported	Supported ($\beta = -.103$, $p < .05$)
H8: IL has a moderating effect on the relationships of AQ(H8a), TR(H8b), IA(H8c), SC(H8d), and HM(H8e) with BFN	Not supported	Not supported

BFN = belief in false news; SI = sharing intent; AQ = argument quality; TR = topical relevance; IA = image appeal; SC = source credibility; HM = homophily; IL = information literacy.

Discussion

The concern about false information is growing worldwide, and related research has been illuminating. In general, studies on this topic have focused on four major themes: defining false or fake information and outlining the extent of this phenomenon (Tandoc et al., 2018; Zannettou et al., 2019); investigating user factors associated with belief in and sharing of false stories (Bronstein et al., 2019); evaluating the impact of fact-checking (Bode & Vraga, 2018; De keersmaecker & Roets, 2017); and mapping the diffusion of false news detection (Shu et al., 2017; Vosoughi et al., 2018). However, to the best of our knowledge, no previous study has employed the ELM to explore the influence of online context factors in this area. Therefore, the current study contributes to the literature by using the ELM to compare the influences of central cues (argument quality and topical relevance) and peripheral cues (image appeal, source credibility, and homophily) on belief in or identification of false information. The moderating role of information literacy on the relationship between informational cues and BFN was also explored. The false news example stimuli were taken from SM or NWs to determine differences in users' information processing model when consuming false stories in different platforms.

The analytical results for both SM- and NW-group models indicated that a user's news SI is highly associated with their belief in the message. This contradicts another study's finding that most tweets are shared by users without reading the contents (Gabielkov et al., 2016). However, this result is consistent with the premise of reasoned behavior theory that suggests a person's behavior is determined by their intention and that this intention is, in turn, a function of their attitude toward the behavior and subjective norms (Fishbein & Ajzen, 1975). Based on this rationale, many researchers have expanded the ELM framework beyond its original focus on attitude formation and thus examined a broader set of outcome variables beyond attitudes (e.g., purchase intention, expectation, information sharing; Kang & Namkung, 2019). This finding suggests that because news SI is associated with belief in the message, the dissemination of false information can be diminished if users are able to discern the falsehood.

About the roles of informational cues, argument quality influences the information processing of false news. The negative relationship between argument quality and BFN in both models indicates that users employ content quality to verify information in both the SM and NW groups. Many ELM-based studies on electronic marketing or shopping have concluded that argument quality persuades consumers to have a favorable attitude toward the product (Cyr et al., 2018; Kim et al., 2016; Meng & Choi, 2019; Wang 2015). However, in the context of news consumption, argument quality enables users to be skeptical about the truth of the content. Topical relevance contributes positively to BFN for SM group, but has no impact for NW group. That is, SM users tend to be vulnerable to believing in false messages when news is topically relevant to them, whereas NW users do not. This can probably be explained by the echo chamber effect. SM users tend to form groups of like-minded people in which favored narratives are promoted, thus polarizing users' opinions and resulting in an echo chamber. In such environments, users continue to consume similar information and tend to generate positive opinions (Del Vicario et al., 2016).

Among the peripheral cues, image appeal has no impact on either model, which differed from the expected outcome. This suggests that the model paths for online persuasion are more complex when different contexts are considered. Source credibility is associated with the perception of false news. Notably, this relationship is positive in the SM group, but negative in the NW group. Thus, users are vulnerable to believing in false news when reading messages from trusted SM contacts, but they tend to identify falsehoods when consuming news from trusted NWs. Similarly, the impact of homophily is negative in the NW group. In general, individuals are more critical when encountering false news on news platforms, but they tend to be vulnerable to believing false news on SM.

Information literacy had a direct effect on BFN in the NW group but not in the SM group. This is consistent with the above finding that individuals tend to be more critical when encountering false news on NWs. Additionally, information literacy was not a moderator for any informational cue. This reveals the urgency of improvements in literacy education, especially when considering the roles of individuals as media gatekeepers in SM.

Conclusion

This study provides theoretical contributions by applying the ELM to explore the influence of online informational cues on the belief in or identification of false news. Findings differ from those of studies investigating marketing or advertising persuasion. Therefore, further research in this area should be considered. Moreover, the results offer two practical implications. First, the online informational cues that are herein proven to influence vulnerability to believing false messages, especially on SM, are analogous to the content and social context bases employed for AI detection; thus, AI detection can be used as an auxiliary method to mitigate the damage caused by fake news. Second, effective training programs may be required for literacy education to combat false news, because information literacy has neither direct nor moderating effect for the SM group in current study.

However, some limitations of this study should be noted. Although the false news stimuli were carefully selected, different stimuli may yield different results because of the varying levels of user knowledge and concern about the topic. In addition, this study used a survey of self-reported data, and the generalizability of the findings is limited to the research context. Source credibility data were also limited to a single survey item. Notably, the utility of PLS path modeling for the SEM approach has been debated. PLS is widely used in management research and in almost all social sciences disciplines. Users believe that its advantages over other analytical techniques include correction for measurement errors and validation of measurement models (Henseler et al., 2014). However, some critics have questioned its statistical underpinnings and its viability as an estimation procedure (Rönkkö, 2014; Rönkkö & Evermann, 2013). To address these concerns, PLS proponents have either refuted arguments based on narrowly conceived simulations and fundamental misconceptions about the purposes and capabilities of PLS (Henseler et al., 2014) or devised other statistical approaches to improve its performance (Evermann & Tate, 2016; Hair, Howard, & Nitzl, 2020; Shmueli, Ray, Velasquez Estrada, & Chatla, 2016). However, these new strategies have not yet been fully evaluated through a comprehensive program of simulation research. Future studies could use versatile modeling techniques to duplicate this study.

Despite these limitations, this study can provide a valuable basis for future investigations to develop more complex and detailed models for exploring additional designs or social elements. Considering using AI technology to combat false news might not only be a question of finding untrue statements, but also of analyzing massive amounts of data regarding social context, or designing features; more research into the topic and the development of feasible countermeasures as valuable references for AI methodology are urgently needed.

References

Allcott, H., & Gentzkow, H. (2017). Social media and fake news in the 2016 election. *Journal of Economic Perspectives, 31*(2), 211–236. doi:10.1257/jep.31.2.211

Angst, C., & Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion. *Management Information Systems Quarterly, 36*(2), 339–373.

Bhattacherjee, A., & Sanford, C. (2006). Influence processes for information technology acceptance: An elaboration likelihood model. *Management Information Systems Quarterly, 30*(4), 805–825.

Bode, L., & Vraga, E. K. (2018). See something, say something: Correction of global health misinformation on social media. *Health Communication, 33*(9), 1131–1140. doi:10.1080/10410236.2017.1331312

Bronstein, M., Pennycook, G., Bear, A., Rand, D. G., & Cannon, T. (2019). Belief in fake news is associated with delusionality, dogmatism, religious fundamentalism, and reduced analytic thinking. *Journal of Applied Research in Memory and Cognition, 8*(1), 108–117. doi:10.1016/j.jarmac.2018.09.005

Chaiken, S., & Maheswaran, D. (1994). Heuristic processing can bias systematic processing: Effects of source credibility, argument ambiguity, and task importance on attitude judgment. *Journal of Personality and Social Psychology, 66*(3), 460–473. doi:10.1037/0022-3514.66.3.460

Chen, C.-Y., & Chang, S.-L. (2019). Self-presentation and counterstereotypic gender strategies in social media campaigning: An example from Taiwan's presidential election. *Journal of Information and Telecommunication, 3*(1), 95–114. doi:10.1080/24751839.2018.1536365

Cheung, C. M. K., Lee, M. K. O., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities. *Internet Research, 18*(3), 229–247.

Cole, S. (2018). *AI-moderators fighting AI-generated porn is the harbinger of the fake news apocalypse*. Retrieved from https://motherboard.vice.com/en_us/article/d3wd3k/gfycat-fighting-ai-porn-deepfakes-fake-news

Cyr, D., Head, M., Lim, E., & Stibe, A. (2018). Using the elaboration likelihood model to examine online persuasion through website design. *Information & Management, 55*(7), 807–821. doi:10.1016/j.im.2018.03.009

De Bruyn, A., & Lilien, G. L. (2008). A multi-stage model of word-of-mouth influence through viral marketing. *International Journal of Research in Marketing, 25*(3), 151–163. doi:10.1016/j.ijresmar.2008.03.004

De keersmaecker, J., & Roets, A. (2017). "Fake news": Incorrect, but hard to correct. The role of cognitive ability on the impact of false information on social impressions. *Intelligence, 65*, 107–110. doi:10.1016/j.intell.2017.10.005

Del Vicario, M., Vivaldo, G., Bessi, A., Zollo, F., Scala, A., Caldarelli, G., & Quattrociocchi, W. (2016). Echo chambers: Emotional contagion and group polarization on Facebook. *Scientific Reports, 6*. Retrieved from https://www.nature.com/articles/srep37825

Evermann, J., & Tate, M. (2016). Assessing the predictive performance of structural equation model estimators. *Journal of Business Research, 69*, 4565–4582.

Fallis, D., & Whitcomb, D. (2009). Epistemic values and information management. *The Information Society, 25*(3), 175–189. Retrieved from https://ssrn.com/abstract=1509163

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Boston, MA: Addison-Wesley.

Gabielkov, M., Ramachandran, A., Chaintreau, A., & Legout, A. (2016). Social clicks: What and who gets read on Twitter? *ACM SIGMETRICS/IFIP Performance*. Retrieved from https://hal.inria.fr/hal-01281190/document

Gefen, D., & Straub, D. W. (2005). A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the Association for Information Systems, 16*, 91–109. doi:10.17705/1CAIS.01605

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research, 109*, 101–110.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Thousand Oaks: SAGE Publications.

Hargittai, E. (2010). Digital na(t)ives? Variation in Internet skills and uses among members of the "net generation." *Sociological Inquiry, 80*(1), 92–113. doi:10.1111/j.1475-682X.2009.00317.x

Henseler, J., Dijkstra, T., Sarstedt, M., Ringle, C., Diamantopoulos, A., Straub, D., . . . & Calantone, R. (2014). Common beliefs and reality about PLS: Comments on Rönkkö & Evermann (2013). *Organizational Research Methods, 17*(2), 182–209.

Jaeger, S. R., & MacFie, H. J. (2001). The effect of advertising format and means-end information on consumer expectations for apples. *Food Quality and Preference, 12*(3), 189–205.

Kang, H., Bae, K., Zhang, S., & Sundar, S. S. (2011). Source cues in online news: Is the proximate source more powerful than distal sources? *Journalism & Mass Communication Quarterly, 88*(4), 719–736. doi:10.1177/107769901108800403

Kang, J.-W., & Namkung, Y. (2019). The information quality and source credibility matter in customers' evaluation toward food O2O commerce. *International Journal of Hospitality Management, 78*, 189–198.

Khan, M. L., & Idris, I. K. (2019). Recognize misinformation and verify before sharing: A reasoned action and information literacy perspective. *Behaviour & Information Technology, 38*(12), 1194–1212. doi:10.1080/0144929X.2019.1578828

Khan, M. L., Wohn, D. Y., & Ellison, N. (2014). Actual friends matter: An Internet skills perspective on teens' informal academic collaboration on Facebook. *Computers and Education, 79*, 138–147.

Kim, M. J., Chung, N., Lee, C. K., & Preis, M. W. (2016). Dual-route of persuasive communications in mobile tourism shopping. *Telematics and Informatics, 33*(2), 293–308.

Kirby, E. J. (2016). The city getting rich from fake news. *BBC.* Retrieved from http://www.bbc.com/news/magazine-38168281

Lazarsfeld, P. F., & Merton, R. K. (1954). Friendship as a social process: A substantive and methodological analysis. In M. Berger, T. Abel, & H. Charles (Eds.), *Freedom and control in modern society* (pp. 18–66). New York, NY: Van Nostrand.

Lazer, D. M., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., . . . & Zittrain, J. L. (2018). The science of fake news. *Science, 359*(6380), 1094–1096. doi:10.1126/science.aao2998

Lee, J., Park, D.-H., & Han, I. (2008). The effect of negative online consumer reviews on product attitude: An information processing view. *Electronic Commerce Research and Applications, 7*(3), 341–352.

Lee, L., Amir, O., & Ariely, D. (2009). In search of Homo economicus: Cognitive noise and the role of emotion in preference consistency. *Journal of Consumer Research, 36*(2), 173–187.

Luna, D., & Peracchio, L. A. (2003). Visual and linguistic processing of ads by bilingual consumers. In L. M. Scott & R. Batra (Eds.), *Persuasive imagery: A consumer response perspective* (pp. 153–175). Mahwah, NJ: Erlbaum.

Mak, B., Schmitt, B. H., & Lyytinen, K. (1997). User participation in knowledge update of expert systems. *Information Management, 32*(2), 55–63.

Marcus, J. (1993). *Mesoamerican writing systems: Propaganda, myth, and history in four ancient civilizations*. Princeton, NJ: Princeton University Press.

McGonagle, T. (2017). "Fake news": False fears or real concerns? *Netherlands Quarterly of Human Rights, 35*(4), 203–209.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology, 27*(1), 415–444.

Meng, B., & Choi, K. (2019). Tourists' intention to use location-based services (LBS): Converging the theory of planned behavior (TPB) and the elaboration likelihood model (ELM). *International Journal of Contemporary Hospitality Management, 31*(8), 3097–3115.

Murphy, M. (2018). Government bans phrase "fake news." *The Telegraph.* Retrieved from https://bit.ly/2yY6ffl

Oyeyemi, S. O., Gabarron, E., & Wynn, R. (2014). Ebola, Twitter, and misinformation: A dangerous combination? Retrieved from https://www.bmj.com/content/349/bmj.g6178

Pennycook, G., Bear, A., Collins, E. T., & Rand, D. G. (2020). *The implied truth effect: Attaching warnings to a subset of fake news stories increases perceived accuracy of stories without warnings.* Retrieved from https://ssrn.com/abstract=3035384

Pennycook, G., Cannon, T., & Rand, D. (2018). Prior exposure increases perceived accuracy of fake news. *Journal of Experimental Psychology: General*, *147*(12), 1865–1880.

Petty, R. E., & Cacioppo, J. T. (1984). Source factors and the elaboration likelihood model of persuasion. *Advances in Consumer Research, 11*, 668–672.

Poor, M., Duhachek, A., & Krishnan, J. S. (2013). How images of other consumers influence subsequent taste perceptions. *Journal of Marketing, 77*(6), 124–139.

Popken, B. (2018). Apologies and promises: Facebook and Twitter tell senators they will do more to combat misinformation. *NBC News.* Retrieved from https://www.nbcnews.com/tech/tech-news/apologies-promises-facebook-twitter-tell-senators-they-will-do-more-n906731

Rivard, S., & Huff, S. (1988). Factors of success for end user computing. *Communications of the ACM, 31*(5), 552–561. doi:10.1145/42411.42418

Rapoza, K. (2017). Can "fake news" impact the stock market? *Forbes.* Retrieved from https://www.forbes.com/sites/kenrapoza/2017/02/26/can-fake-news-impact-the-stock-market/#743c0ed42fac

Rönkkö, M. (2014). The effects of chance correlations on partial least squares path modeling. *Organizational Research Methods, 17*(2), 164–181.

Rönkkö, M., & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. *Organizational Research Methods, 16*(3), 425–448. doi:10.1177/1094428112474693

Shaban, H., Timberg, C., & Dwoskin, E. (2017). Facebook, Google and Twitter testified on Capitol Hill. Here's what they said. *Washington Post.* Retrieved from https://www.washingtonpost.com/news/the-switch/wp/2017/10/31/facebook-google-and-twitter-are-set-to-testify-on-capitol-hill-heres-what-to-expect

Shi, J., Hu, P., Lai, K., & Chen, G. (2018). Determinants of users' information dissemination behavior on social networking sites: An elaboration likelihood model perspective. *Internet Research, 28*(2), 393–418.

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Evaluating the predictive performance of PLS models. *Journal of Business Research, 69*(10), 4552–4564.

Shu, K., Sliva, A., Wang, S., Tang, J., & Liu, H. (2017). *Fake news detection on social media: A data mining perspective.* Retrieved from https://arxiv.org/abs/1708.01967

Steffes, E. M., & Burgee, L. E. (2009). Social ties and online word of mouth. *Internet Research, 19*(1), 42–59.

Susarla, A. (2018). *How artificial intelligence can detect—and create—fake news*. Retrieved from https://msutoday.msu.edu/news/2018/how-artificial-intelligence-can-detect-and-create-fake-news/

Tandoc, E. C., Lim, Z. W., & Ling, R. (2018). Defining "fake news." *Digital Journalism, 6*(2), 137–153. doi:10.1080/21670811.2017.1360143

Thorson, E. (2008). Changing patterns of news consumption and participation. *Information, Communication & Society, 11*(4), 473–489. doi:10.1080/13691180801999027

Townsend, C., & Kahn, B. E. (2014). The "visual preference heuristic": The influence of visual versus verbal depiction on assortment processing, perceived variety, and choice overload. *Journal of Consumer Research, 40*(5), 993–1015. doi:10.1086/673521

UNESCO. (2018). *Journalism, fake news & disinformation.* Retrieved from https://en.unesco.org/sites/default/files/journalism_fake_news_disinformation_print_friendly_0.pdf

Urbach, N., & Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *Journal of Information Technology Theory and Application, 11*(2). Retrieved from https://aisel.aisnet.org/jitta/vol11/iss2/2

Van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2009). Using the Internet: Skill related problems in users' online behavior. *Interacting With Computers, 21*, 393–402. doi:10.1016/j.intcom.2009.06.005

Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science, 359*(6380). Retrieved from https://science.sciencemag.org/content/359/6380/1146

Wang, P. (2015). Exploring the influence of electronic word-of-mouth on tourists' visit intention: A dual process approach. *Journal of Systems and Information Technology, 17*(4), 381–395.

Wardle, C. (2017). *"Fake news." It's complicated*. Retrieved from https://medium.com/1st-draft/fake-newsits-complicated-d0f773766c79

Wu, L., Morstatter, F., Hu, X., & Liu, H. (2016). Mining misinformation in social media. In M. Thai, W. Wu, & H. Xiong (Eds.), *Big data in complex and social networks* (pp. 1–34). Boca Raton, FL: Taylor & Francis Group.

Xu, X., & Huang, Y. (2019). Restaurant information cues, diners' expectations, and need for cognition: Experimental studies of online-to-offline mobile food ordering. *Journal of Retailing and Consumer Services, 51*, 231–241.

Zannettou, S., Sirivianos, M., Blackburn, J., & Kourtellis, N. (2019). The web of false information: Rumors, fake news, hoaxes, clickbait, and various other shenanigans. *Journal of Data and Information Quality, 11*(3). Retrieved from https://arxiv.org/abs/1804.03461

Zubiaga, A., & Ji, H. (2013). *Tweet, but verify: Epistemic study of information verification on Twitter.* Retrieved from https://arxiv.org/abs/1312.5297

Appendix: Survey items

BFN
I believe the information is truthful.

SI
I would like to share the information.

Argument quality
AQ1: The information is informative.
AQ2: The information is helpful.
AQ3: The information is valuable.
AQ4: The information is persuasive.

Topical relevance
TR1: I am always interested in this topic.
TR2: The topic is relevant to me.

Image appeal
IA1: The images used in the information are appropriate.
IA2: The images used in the information are interesting.
IA3: The images used in the information make the content look appealing.
IA4: The images used in the information appeal to me emotionally.

Source credibility
SC1: The source of the information is reliable.
SC2: The platform where the information is posted is trustworthy. (Omitted)

Homophily (the SM group)

HM1: I have good relationships with people on LINE or Facebook.

HM2: I enjoy reading news stories shared by people on LINE or Facebook.

Homophily (the NW group)

HM1: The website is attractive to me.

HM2: The website often express similar attitude to mine.

Information Literacy

IL1: I can search for online information when I need to.

IL2: I contribute to online discussion in the form of writing comments when I need help.

IL3: I verify online information when I am not sure about its authenticity.